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Quantifying Speech Rhythms: Perception and Production Data in the Case of Spanish, Portuguese, and English

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by

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ABSTRACT

Quantifying speech rhythms: Perception and production data in the case of Spanish, Portuguese, and English,

by

Michael Joseph Harris

This dissertation addresses the methodology used in classifying speech rhythms in order to resolve a long-standing linguistic conundrum about whether languages differ rhythmically. There is a widespread perception, both among linguists and the general population, that some languages are stress-timed and others are syllable timed. Stress-timed languages are described as having less-regular rhythms, as syllable durations vary according to the placement of stress in the phrase. Meanwhile, syllable-timed languages are described as displaying less variation in rhythm, which syllable durations being more regular. This dissertation quantitatively evaluates these described rhythmic differences in Spanish, Portuguese, and English. The first chapter introduces speech rhythms and reviews past literature on their perception and production. The second chapter evaluates a widely used metric of speech rhythms, the PVI, and determines that it is not effective in distinguishing between two dialects of Spanish. The third chapter compares the speech rhythms of Mexican and Chicano Spanish. This chapter concludes that Chicano Spanish is more restricted in its vowel duration variability, while Mexican Spanish employs both highly variable durations (i.e. stress-timed) and highly uniform durations (i.e. syllable-timed). The

fourth chapter describes a perception study used to compare the speech rhythms of Spanish, English, and Portuguese, and shows that these languages' rhythms do not always group according to language. In the fifth chapter, I describe a study of the production of the same utterances initially used in the perception experiment; this allows an analysis of what prompts the perceptual differences in speech rhythm described in Chapter Four. The sixth and final chapter discusses the implications and applications of these findings and gives direction for further investigation. Although both production and perception studies of speech rhythms have been performed in the past, my dissertation expands these methodologies by combining production and perception data is a single analysis. I use perception data to relatively classify the rhythms of utterances through low-pass speech filtering, then analyze the production of these data computationally to provide a more complete perspective of what prompts differences in speech-rhythms and how Spanish, Portuguese, and English data relate rhythmically. Thus, my dissertation is thorough, while still addressing traditional rhythm metrics and employing current computational methodology. It seeks to challenge linguists' methodologies in quantitatively addressing speech rhythms, and to further clarify the position of Spanish, Portuguese, and English on the speech rhythm continuum.

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Chapter 1

An Introduction to Speech Rhythms

Overview

This chapter presents an overview of past speech rhythm research. It begins by explaining the basic concept of speech rhythm and addressing the distinction between syllable and stress-timed languages (and briefly mention mora languages). It then addresses the importance of speech rhythm research. The following sections review production speech rhythm studies and perception rhythm studies; the methodological implications of these studies to my dissertation are also discussed.

1.1. Speech Rhythm Distinctions

Pike (1945) described the simple rhythm units of languages: stress-timed and syllable-timed. The former means that the duration of syllables varies according to the placement of stress and seem to be less uniform throughout the entire phrase; languages that sound more stress-timed include, for example, Dutch and English. The latter means that syllable duration is relatively uniform within a phrase, as in French and Spanish. In addition to the two rhythm classes described by Pike (1945), a third rhythm class, mora-timed speech has been identified, which uses moras, i.e. phonological weight units, in the processing of languages and exists, for instance, in Japanese (Otake, Hatano, Cutler, and Mehler 1993). As mentioned, one basic reasoning behind the nature of this rhythmic difference is that various languages privilege, or give spectral prominence to different phonological units: the mora, the syllable, or the stress foot (Lee and Todd 2004). This would account for the

existence of these rhythmic differences as well as their relevance in parsing speech (in the recognition of word boundaries for instance).

For quite some time, this perceived difference in speech timing was regarded as a dichotomy: "As far as is known, every language in the world is spoken with one kind of rhythm or with the other" (Abercrombie 1967:97). Dasher and Bolinger (1982) suggested that stress-timing and syllable-timing can be correlated to specific phonological phenomena in a given language. Specifically, they suggested that stress-timed languages present a greater variety of syllable types, and have greater vowel reduction between stress and unstressed vowels. Dauer (1987) agreed that speech rhythms are a product of their phonological properties, but added that languages should not be thought of as either stress-timed or syllable-timed, but instead should be conceived on a continuum, with the most stress-timed languages at one extreme of the continuum and the most syllable-timed languages at the other extreme. While some languages – e.g., Spanish and English – exist near the opposite ends of this continuum, other languages exist somewhere in the middle, exhibiting some syllable-timed characteristics and some stress-timed characteristics. Catalan, for instance, has simple syllable types but also exhibits vowel reduction, causing it to fall somewhere between stress-timed and syllable-timed on the continuum (see Table 1). Dauer (1987) also concluded that simple measures of interstress intervals or syllable durations were not effective in assigning rhythm class, demonstrating the necessity of a measure of speech rhythms with more discriminatory power.

Poles of Rhythm Continuum	More Syllable Timed		More Stressed Timed
Proposed phonetic characteristics	less variable segment durations		more variable segment durations
Example Languages	Spanish	Catalan	English

Table 1.1: An illustration of the speech rhythm continuum

1.2. The Importance of Speech Rhythm Research

The fact that languages differ rhythmically is a widespread intuition (Loukina, Kochanski, Rosner, and Keane 2011). Most linguists, and even most humans, agree that they perceive some rhythmic difference in the production of certain languages; however, the results of linguistic studies on both the perception and production of speech rhythms have failed to support this with conclusive empirical evidence (although many studies have shown some evidence of rhythmic variation between languages, e.g. Low and Grabe 1995). Nevertheless, linguists have recently expanded methodologies in their attempts to quantify rhythmic differences between languages or dialects. In addition to the perceived differences between two languages, three factors suggest that there is some fundamental rhythmic variation in speech.

Firstly, consider early studies investigating whether or not an “underlying pattern” determines the timing between sequential segments in an utterance, or whether this rhythm is simply a random artifact of the time it takes to finish articulating the previous segment in the utterance. For instance, Ohala (1975) offers three hypotheses for the factors that determine the timing of speech; these hypotheses consider the sentence 'Joe took father's shoebench out':

> "1. Some units of speech, perhaps syllables, stresses or morae, are uttered in time to some underlying regular rhythm, e.g. the [b] of 'shoebench' will be uttered after the [dʒ] of 'Joe' an interval which is an integral multiple of the period of this underlying rhythm.
>
> 2. The units of speech are executed according to some underlying pre-pro grammed time schedule although there may be no isochrony in this schedule.
>
> 3. There is no underlying time program or rhythms; a given speech gesture is simply executed after the preceding gestures have been successfully completed, that is, one unit is simply strung after the other." (Ohala 1975:431- 432).

He notes that while Hypothesis 1 has been assumed by some linguists, it proves difficult to verify via empirical data. This would suggest that speech timing is either completely random, or executed according to some 'schedule', but is not isochronous. Given that Ohala (1975) investigates English and Japanese, which are said to be stress-timed and mora-timed respectively, this is compatible with traditional rhythm classes. Meanwhile, he mentions that previous studies measuring the time intervals between certain speech events, such as voiceless stops or successive jaw openings suggest that there is an underlying pattern or schedule to speech timing, which is to say that Hypothesis 2 rather than Hypothesis 3 is more likely. Specifically, Kozhevnikov and Christovich (1965), Allen (1969), Lehiste (1971, 1972) found evidence for Hypothesis 2 as an underlying pattern in speech by showing that segments in an utterance tend to contribute equally to the variance in timing between segments of the utterance (as cited in Ohala 1975:439).

This further supports the concept that some sort of pattern exists in the timing or rhythm of speech.

Secondly, various studies have shown that neonates and infants can distinguish between languages of two different rhythm classes, but not necessarily between two languages of the same rhythm class (e.g. Nazzi, Bertoncini, and Mehler 1998). This suggests that a patterned speech timing not only exists, but varies across language or dialect. In this study, French newborns were able to discriminate between stress-timed English and mora-timed Japanese, but not between two stress-timed languages (English and Dutch) in a task that evaluated infants' responses to the language stimuli via a pacifier that measured the amplitude of the infants' sucking. High amplitude sucking represented a reaction to the language stimuli and the infants reacted with higher amplitude sucking to the English stimuli as compared to the Japanese, but did not show a significant difference in sucking amplitude for the English as compared to the Dutch stimuli (Nazzi, Bertoncini, and Mehler 1998). These experiments not only suggest that languages do differ rhythmically, but also that infants begin to exploit rhythmic cues at a young age. Thus, rhythms may be instrumental in parsing words, perhaps because they give prominence to the syllable structure (in so-called syllable-timed languages) or the stress patterns (in so-called stress-timed languages). Thirdly, Wretling and Eriksson show that speech impersonators could alter spectral characteristics, but less so timing at the phoneme and word levels in imitating speech, suggesting that rhythm is somehow "hard coded" in the adult speaker (1998:1). Thus, while there is ample evidence for the existence of cross-linguistic rhythmic differences, their study via empirical methodology has proved more elusive.

The particular importance of speech rhythms to our understanding of prosody, and the ability to dissect a particular area of linguistics in general, is self-evident. Subjected to measurement for about 70 years, and more intensively so in the past three decades, linguists still fail to agree on just what speech rhythms are, much less how they can be quantified. In an introduction to a special edition of *Phonetica* dedicated to speech rhythms, Kohler (2009) outlines the centrality of the topic and its current state:

> Speech rhythm has been a topic at all the International Congresses of Phonetic Sciences since 1979. Initially, it was discussed under the heading of *Temporal Relations within Speech Units*, at a Symposium at Copenhagen... The topic was continued under various headings and in various forms: an Oral Session *Temporal Organization of Speech* at Utrecht in 1983, a Symposium *Rhythm and Metrics* and an Oral Session *Metrical Theory* at Tallinn 1987, an Oral Session *Timing and Rhythm* at Aix-en-Provence in 1991, a Poster Session *Stress and Timing* at Stockholm in 1995, Poster Sessions *Intonation: Rhythm I, II, III* at San Francisco in 1999, an Oral Session and a Symposium (organized by Pier Marco Bertinetto) *Stress and Rhythm*, and an Oral Session *Prosody: Rhythm and Phrasal Structure* at Barcelona in 2003, an Oral Session *Stress and Rhythm* at Saarbrücken in 2007. The papers in these sessions do not form homogeneous packages of rhythm research but are a mix of questions of segmental timing, stress, intonation, and rhythm under the labels of stress- and syllable-timing. (2009:8-9).

Indeed, the current state of speech-rhythms could be more easily summarized by the areas in which linguists differ rather than by which they agree. A widespread attempt to quantify speech rhythm production has led to the development of metrics (usually related to segment variability, e.g. Low and Grabe 1995, Deterding 2001) that reportedly compare the rhythms of languages or dialects. Some of these metrics have been adopted in the past because they were easy to calculate; in some cases they do crudely approximate supposed differences in speech-rhythms, although they only encapsulate a small segment of rhythmic perception (Arvaniti 2009). However, current studies point to the necessity of aligning perception and production data (e.g. Barry, Adreeva, and Koreman 2009), of doing so in a more statistically sound manner, and including all relevant information (e.g. Loukina, Kochanski, Rosner, and Keane 2011).

In fact, regardless of methodological differences, one central fact has become clear in recent literature: in attempting to find acoustic evidence of a perceived difference in speech rhythms, it is not enough to simply use those interval metrics that appear to conveniently reflect perception. This is to say that certain metrics that have been applied to speech rhythm discrimination studies appear to (at least partially) reflect differences between two languages that are traditionally described as belonging to different rhythm classes. Nonetheless, it is hasty to adopt a metric for quantifying speech rhythms simply because it classifies Spanish as more syllable-timed than English, for instance. First one must determine what exactly the metric measures. For instance, is vowel duration variability truly akin to perceived rhythmic differences? Also, is the manner in which these metrics are measured, calculated, and reported statistically sound? In fact, as we will see in the following chapters, many traditional metrics are not exhaustively informative to

rhythmic differences for several reasons. Firstly, as **Chapters 2** and **3** will describe in detail, some of these metrics are not calculated in a statistically sound manner, and fail to address a full-range of word-frequencies. Equally troubling is the fact that many of these metrics are presented as a single value intended to address, for instance, the vowel duration variability of an entire phrase, a speaker, or even a speaker type. This occurs in the presentation of a mean PVI value, or a single standard deviation of vowel durations. Finally, the assumption that, say, Spanish and English belong to different rhythm classes, so *all* utterances of Spanish differ from *all* utterances of English has certainly never been proven. In fact, rhythmic variation in speakers appears to contribute a great deal to certain interval metrics, regardless of rhythm class (e.g. Loukina *et al.* 2009). In fact, up to this point, it has not been proven that Spanish does in fact differ from English in terms of syllabic rhythm; hence the need for the current dissertation.

To begin to address these issues, one must critically assess the utility of these measures in a multifactorial manner, allowing for non-linear trends and interactions between metrics of speech rhythm (see **Chapter 3**). This approach allows one to consider multiple factors that may contribute to our perception of speech rhythms. Cues of duration variability, and vowel duration variability in particular have been reported to affect rhythmic perception (e.g. Low and Grabe 1995; Deterding 2001). However, other factors potentially contribute to speech rhythms as well. For instance, other prosodic cues, F0 and intensity, have been shown to work with segment duration to indicate lexical stress. While these are not strictly considered to contribute to rhythm, it is certainly a possibility that they may play a role in our perception of rhythmic differences; this possibility is explored in **Chapter 5**. Meanwhile, corpus-based frequencies have been shown to effect various

aspects of pronunciation (e.g. Bell et al. 2009), so it is conceivable that rhythms (or cues that effect the perception of rhythms) vary with frequency. This possibility is explored further in **Chapters 3** and **5**. By using various sophisticated statistical approaches to rhythmic data, it is possible to avoid, or at least minimize such methodological pitfalls.

1.3. Production Speech Rhythm Studies[1]

As a result of the continuous view of speech rhythms (e.g. Dasher and Bolinger 1982), linguists sought to relatively classify the production of language rhythms. That is, rather than classify a language as either (absolutely) syllable-timed or (absolutely) stress-timed, languages or varieties/dialects of languages were compared to other languages or other varieties/dialects of the same language. Low and Grabe (1995) made significant strides in the study of speech rhythms in their study of prosodic patterns in Singapore English compared to British English. This study is significant in focus and methodology. Firstly, it examined two varieties of the same language, comparing native (L1) and second language (L2) English speakers. Secondly, it introduced the Pairwise Variability Index (henceforth the PVI, *see* **Appendix 1, Section 2**) as a new measure intended to relatively classify speech rhythms by measuring the variation between successive sets of vowels as opposed to the more limiting measure of overall variation within a phrase (as cited in Carter 2007:5). This study served to provide a framework for further speech rhythm studies and studies of cross-varietal speech rhythms of a single language in particular.

The PVI (see Figure 1.1) is the measure of the absolute difference of the vowel duration of two adjacent syllables divided by the average vowel duration of the same two

[1] A variety of metrics have been suggested as quantifiers of speech rhythms. The metrics in this section are calculated on two different ranges of vowel durations in Appendix A.

adjacent syllables; thus, a sentence with *n* syllables yields *n*-1 PVIs. These PVIs represent the variability of vowel duration, with lower PVIs representing a more syllable-timed language and higher PVIs representing a more stress-timed language.

$$PVI = \frac{|(vowelduration_1 - vowelduration_2)|}{mean(vowelduration_1, vowelduration_2)}$$

Figure 1.1: Equation for calculation of PVI (e.g. Low and Grabe 1995), also knows as the *n*PVI (Low Grabe, and Nolan 2000).

Consider Figure 1.2. The top panel denotes the approximate vowel durations of a stress-timed language, English, while the lower panel represents the vowel durations of a syllable timed language, Spanish. The PVI scores for the top panel would be higher, due to the higher variability of vowel durations, and compared to the lower panel. If vowel duration variability is indeed a reflection of rhythm class distinctions, Low and Grabe's (1995) PVI would reflect this difference, with the stress-timed language in the top panel displaying a higher PVI as compared to the syllable-timed language in the lower panel. It is important to note three things.

First, PVIs do not represent an index of 'the absolute rhythm of a language' – instead, they allow the comparison of the rhythms of two or more languages or varieties. Second, the PVI has been reported as a mean for each utterance (or even a speaker, e.g. Grabe and Low 2002), rather than a series of individual PVI scores (*see* **Chapter 2**). Thirdly, these spectrograms are meant as a representation of how the PVI works; such short phrases are certainly not indicative of the overall rhythmic nature of a language or even a speaker. In fact, it is possible to choose two phrases from the same speakers that

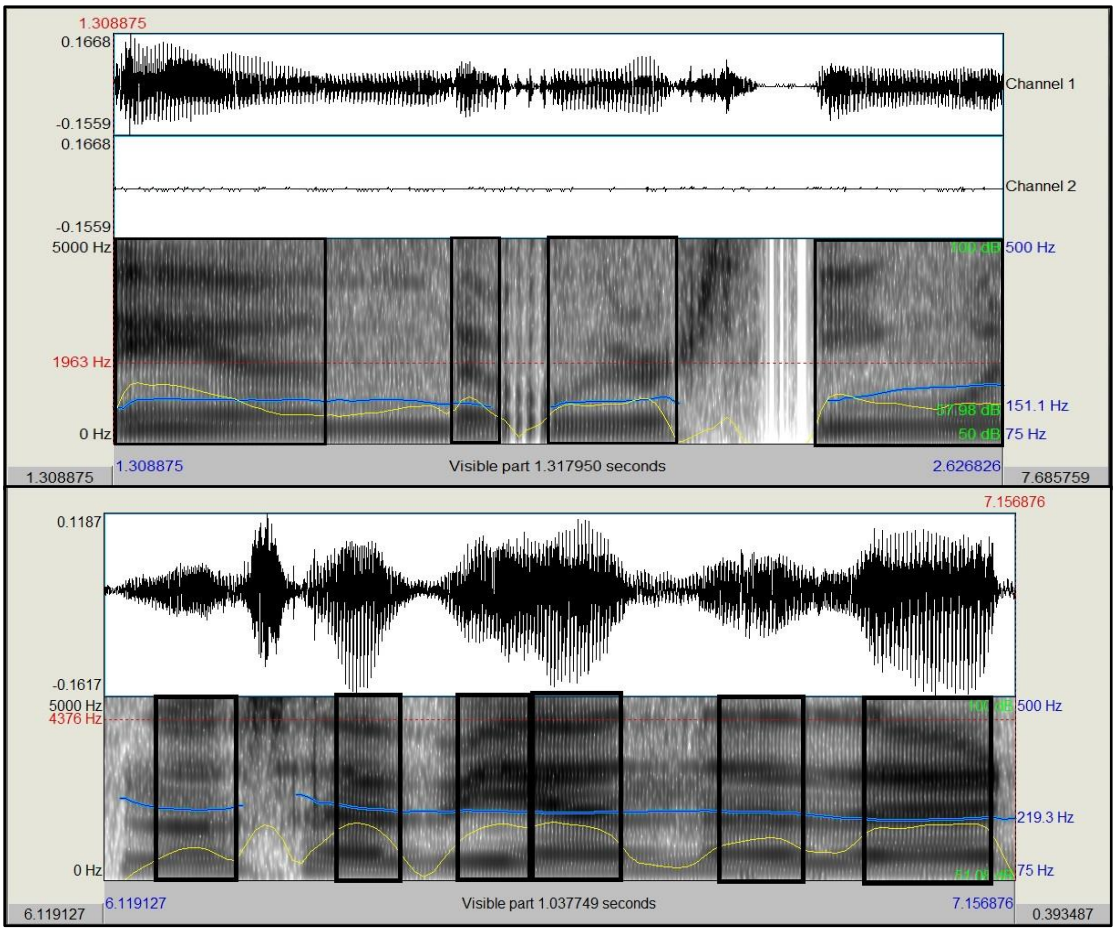

Figure 1.2: Waveforms and spectrograms of naturalistic speech of monolingual female American English (top panel) and monolingual female Mexican Spanish (lower panel). The phrase in the top panel is "*and we were skiing* " The phrase in the lower panel is "*no sabía nadar*". The approximate vowel lengths are marked by the black boxes.

show the opposite trend, with less vowel duration variability in English as compared to Spanish (see Figure 1.4 below).

Although the PVI was adopted by many linguists as an apparently transparent and accurate method of comparatively classification of speech rhythms, other metrics were also proposed under the heading of *interval measures* (or IMs, to use White and Mattys's (2007) term). Specifically, Ramus, Nespor, and Mehler (1999) defended the use of three variables in order to determine the rhythm of a language:

- the percentage of a sentence taken up by vowel duration (%V);
- the average standard deviation of vowel duration (ΔV); and
- the average standard deviation of consonant duration (ΔC).

(*see* **Appendix 1, Section 3**, **4**, and **5**, respectively). However, in applying these metrics, Ramus et al. (1999) suggest that only %V and ΔC reflect differences in speech rhythms.

Deterding (2001) proposed measuring the duration of the entire syllable, rather than only the vowel duration, arguing that some syllables may be longer than others regardless of the presence of vowels. The author used a normalizing equation for syllable length similar to the PVI called the Variability Index (VI).

Low, Grabe, and Nolan (2000) revisited speech rhythms of Singapore and British English and discussed the application of speech-rate normalization to the PVI. That is, the authors differentiated between the PVI as in Figure 1.1 (from Low and Grabe 1995), which they called *n*PVI, for normalized PVI, and the *r*PVI, or raw PVI, calculated as in Figure 1.3 below. As with the *n*PVI, Low, Grabe, and Nolan presented the *r*PVI as a mean of a series of PVI values for an utterance.

$$PVI = |(vowelduration_1 - vowelduration_2)|$$

Figure 1.3: Equation for calculation of *r*PVI (Low, Grabe, and Nolan 2000).

Low, Grabe, and Nolan (2000) argue that the *n*PVI is superior as it normalizes the metric for differing speech rates between speakers. The vast majority of linguists have adopted

the *n*PVI, eschewing the *r*PVI completely. Thus, for the remained of this dissertation, the term PVI will refer to *n*PVI (unless otherwise noted), as in Figure 1.1.

While Low, Grabe, and Nolan (2000) compared first language (L1) speakers and second language (L2) speakers, the more recent studies of Carter (2005, 2007) as well as Fought (2003) investigated bilingual Chicano speakers of Spanish and English. Bunta and Ingram (2007) also examined the acquisition of Spanish-English bilingual speech rhythms in children using vocalic and intervocalic PVI values, and concluded that bilingual and monolingual speakers differ in speech rhythms, particularly in the youngest participants, age approximately 4 years, although these differences diminished for older speakers.

White and Mattys (2007), undertook a more exhaustive investigation of the relative merits of the PVI and other IMs by applying both normalized and raw pairwise variability indices as well as the IMs suggested by Ramus et al. (1999) to both cross-varietal and cross-language utterances. Additionally, they tested the correlation of these metrics with speech-rate, exploring the effectiveness and/or necessity of rate-normalization measures. Although previous studies had compared competing metrics of duration variability (e.g. Low et al. 2000), White and Mattys' (2007) study was more comprehensive: their goal was to compare the metrics used to classify duration variability, as opposed to dedicating their work to the sole task of classifying the rhythms of specific languages or varieties. The study concluded that the rate-normalized *n*PVI, the rate-normalized standard deviation of vowel duration VarcoV, as well as the percentage of an intonational unit comprised by vowels best distinguished between syllable and stress-timed languages as well as between L1 and L2 speakers.

Even though White and Mattys (2007) constitutes important progress, it still leaves room for improvement in several areas. First, the statistical assessment of the performance of the metrics is incomplete; they report whether or not certain effects are significant, but fail to report the relative strength of each effect. Thus, one cannot evaluate the relative statistical performance of each metric due to their failure to report R^2-values, beta coefficients, etc. Furthermore, their exploration does not include a truly multifactorial analysis, which could potentially reveal a far more complex picture of the behavior of the metrics. Secondly, a specific weakness of the PVI, is mentioned by the authors: "PVI scores derived alternating patterns and monotonic geometric series may be the same, so that, for example PVI(2, 4, 2, 4, 2, 4) and PVI(2, 4, 8, 16, 32, 64) are equal" (White and Mattys 2007:519). While White and Mattys (2007) mention this weakness, they make no suggestions for the improvement of this metric.

Chapters 2 and **Chapter 3** will discuss the PVI in more depth. This is particularly important as it has been so widely adapted in speech rhythm research. These two chapters will assess the utility of the PVI (amongst other metrics, e.g. **Chapter 3**) is distinguishing between two dialects of Spanish: monolingual Mexican Spanish and bilingual Chicano Spanish. **Chapter 2** identifies some shortcomings in the utility of the PVI, particularly in its failure to account for the great of amount of variation in vowel durations that occurs for each participant. **Chapter 3** goes on to compare the PVI to other IMs in a multifactorial analysis and determines that it is less effective in distinguishing between the two dialects of Spanish. In fact, it shows that the PVI is only effective in a rather small range of word frequencies.

A few speech rhythms studies have employed more statistically advanced methodology (as compared to the aforementioned study). In particular, Loukina, Kochanski, Shih, Keane, and Watson (2009) used automatic segmentation of durations, rather than the manual segmentation employed in most rhythm studies (e.g. Low and Grabe 1995). This study evaluates 15 interval metrics in classifying the speech rhythms of English, Greek, Russian, French and Mandarin. This automatic segmentation allowed the authors to evaluate larger corpora; they conclude that while there is a fair amount of rhythmic variation between languages, there is also a comparable amount of variation within languages. Some IMs did appear to be more effective in distinguishing rhythms, but there is no single metric that consistently distinguishes between the rhythms of the various languages examined. The authors conclude that speech rhythms are a two or three-dimensional phenomenon (Loukina et al. 2009:1534).

Callier (2011) applies the PVI of syllable duration and a speech rate normalized standard deviation of syllable durations (VARCOS) in order to examine the Mandarin of six Chinese characters from the same show. Callier suggests that some sociolinguistic factors may be relevant in determining both the rhythm and final syllable lengthening of the utterances examined. The only sociolinguistic factor related to rhythm discussed was gender. The three female characters show greater syllable duration variability than the three male characters in terms of PVIS. The author compares this increased duration variability in women to “the widespread impression of women’s pitch and intonation as highly dynamic or “swoopy” (Henton 1995).” (Callier 2011:48).

Harris and Gries (2011) apply multifactorial methodology and corpus-based frequency effects in their evaluation of the efficacy of various metrics in distinguishing

the speech rhythms of Chicano and Mexican Spanish. Their conclusions regarding IMs is in agreement with those of Loukina *et al*. (2009), namely that no single IM is sufficient in distinguishing speech rhythms. Furthermore, they show a) that it is necessary to include corpus-based frequency effects in speech rhythm analysis, as frequency affects duration cues, and b) it is necessary to use a multifactorial approach in the analysis of IMs, as it is possible to see interactions, as well as main effects. Loukina et al. (2011) are largely in agreement with Loukina et al. (2009); in examining the efficacy of various IMs in distinguishing five languages in a spoken corpus; no single rhythm measure was successful in discerning between all five languages.

The failure of any single IM to distinguish between languages according to speech rhythm is not entirely surprising. Compare Figure 1.4 to Figure 1.2 above and recall that the PVI and other metrics of speech rhythms are largely based upon the concept that stress-timed languages will display more variable interval (and especially vowel) durations as compared to syllable-timed languages. As Figure 1.4 shows, this trend varies with speaker performance. The stress-timed English in the top panel displays quite regular vowel durations as compared to the syllable-timed Spanish in the lower panel. Given that there is a fair amount of rhythmic variation within languages (e.g. Loukina *et al*. 2009), the reliability of any measure based on interval durations as a correlate of speech rhythms is certainly questionable.

Beyond traditional IMs, several studies have suggested that additional cues, including intensity and spectral prominence can help determine rhythm (e.g. Lee and Todd 2004). Kochanski, Loukina, Keane, Shih, and Rosner (2010) show that the acoustic properties of segments can be predicted from preceding segments, and extend into a

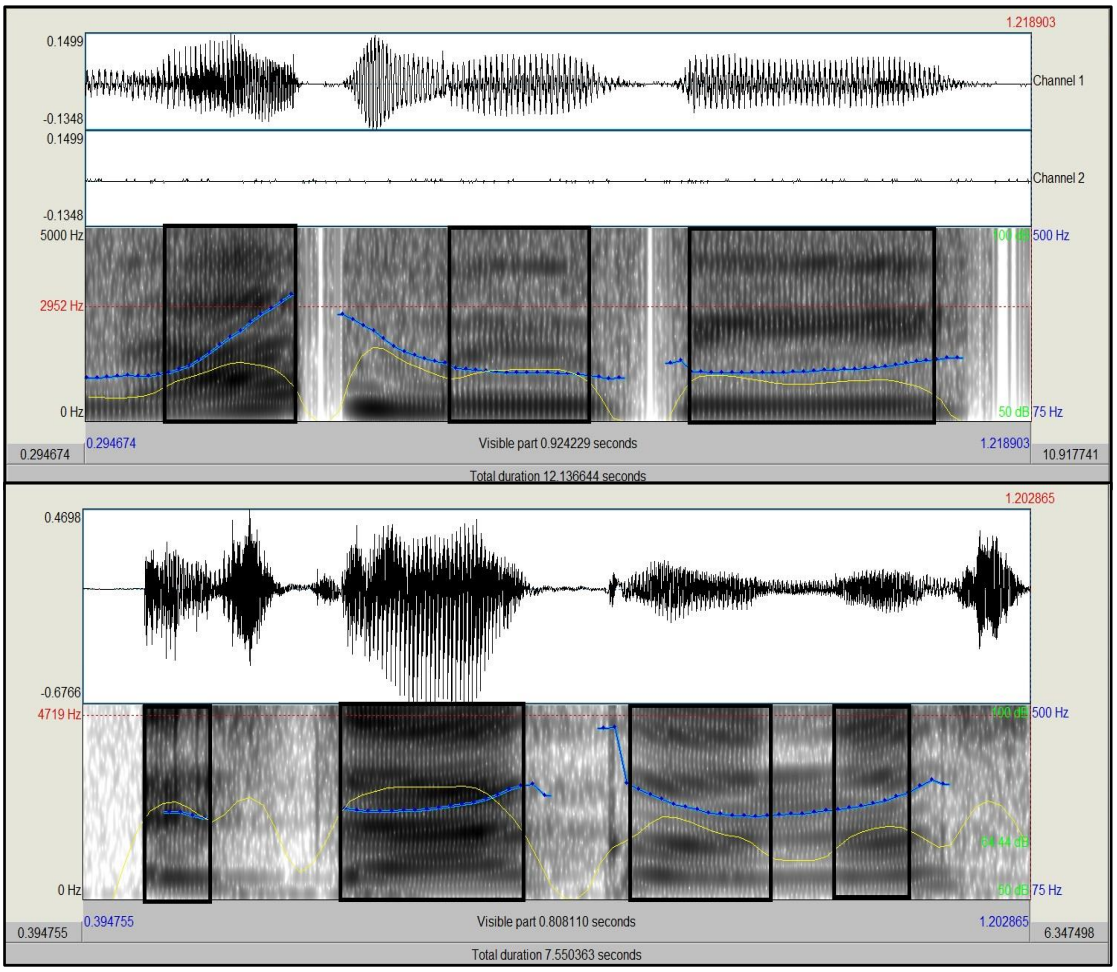

Figure 1.4: Waveforms and spectrograms of naturalistic speech of monolingual American English (top panel) and Mexican Spanish (lower panel). The phrase in the top panel is "*that movie*" (note slower speech and phrase-final lengthening). The phrase in the lower panel is "*esta(b)a con (u)nos*".The approximate vowel lengths are marked by the black boxes.

relatively large range of preceding segments, suggesting that some properties of language rhythms can be predicted by segments surrounding the segment being measured. Specifically, they showed that across 4 languages (Greek, French, English, and Taiwanese Mandarin), vocalic and consonantal durations could be predicted by both the duration of the preceding segment, as well as the preceding seven segments. The amount of variance explained by these segments did vary widely. In fact, in some cases the amount of variance explained was negligible by the authors' own admission, and even those portions

that fared better were not extremely well-explained by the predictors; the maximum coefficient of determination r^2 was 43%. Not surprisingly, the portions of the corpus that consisted of participants reading poetry were better by surrounding segments, as compared to those portions where participants read prose.

Thus, while it is certain that acoustic cues contribute to the intuition that languages differ rhythmically, not only is there a lack of consensus as to which cue(s) do contribute to this perceived difference and how one would quantify this difference, but it appears that these cues behave in a multidimensional manner (Loukina et al. 2009) and do not affect words of different frequencies in the same manner (Harris and Gries 2011).

1.4. Speech Rhythm Discrimination Studies

In addition to the ever-increasing body of works attempting to identify and implement interval measures in the classification of the production of speech rhythms, there has also been a simultaneous (although admittedly smaller) effort to evaluate the perception of speech rhythms. These experiments determine if participants can discriminate between languages of different rhythm classes. They have been performed with infant participants (e.g. Christophe and Morton 1998) and adult participants (e.g. Ramus and Mehler 1998). The stimuli used in speech rhythm discrimination studies include unaltered recorded speech (in the case of infants, e.g. Christophe and Morton 1998), low-pass filtered speech (Mehler et. al. 1998), and resynthesized speech (e.g. Ramus and Mehler 1999). In the case of the latter two stimuli, recorded speech is altered in a manner that reportedly preserves syllabic rhythm while degrading other acoustic cues that may allow language discrimination; this will be referred to as utterance degradation in the current chapter. The

remainder of this section will discuss speech rhythm discrimination studies and the implications of these works on the methodology of this dissertation. It will first present the stimuli used in various speech rhythm discrimination studies (unaltered utterances, low-pass filtered utterances, and resynthesized utterances). Each of these methodologies will be exemplified by noteworthy studies that employ these approaches. It will then address a methodological debate, namely whether low-pass filtered stimuli are superior to resynthesized stimuli in speech rhythm perception experiments. These discussions are relevant to the methodologies employed in later chapters, and especially in **Chapter 4**, where a speech rhythm discrimination task with English, Portuguese, and Spanish stimuli is conducted.

As previously mentioned, a major argument for the existence of speech rhythms is the fact that infants and neonates appear to distinguish between languages based solely upon rhythmic information (the rhythm hypothesis). It is accepted that infants can distinguish between their mother tongue and a foreign language, or are sensitive to the 'foreignness' of a language (e.g. Christophe and Morton 1998). In fact, this ability has been demonstrated in fetuses as well (e.g. Kisilevsky et al. 2009). It has been hypothesized that infants exploit rhythmic cues in this language discrimination (given that fetuses are also capable of distinguishing between their maternal language and a foreign language as mentioned, it is possibly, and even probable that rhythm sensitivity begins in-utero). Due to infants' hypothesized abilities to distinguish between languages of different rhythm classes, they have been the subject of speech rhythm perception experiments. When using infant participants, it is theoretically possible to use unaltered speech stimuli, which is not possible in the case of older participants. In addition, utterance degradation

has been used in the case of infants as well as adults. For instance, Nazzi, Jusczyk, and Johnson (2000) showed that five-month old children are able to discriminate between unaltered Japanese and English (mora-timed and stress-timed respectively) and low-pass filtered Japanese and Italian (mora-timed and syllable-timed respectively, more on low-pass filtering below). These results are in agreement with Nazzi et al., who, studying language discrimination of low-pass filtered utterances by newborns, concluded that "newborns use prosodic and, more specifically, rhythmic information to classify utterances into broad language classes defined according to global rhythmic properties" (1998:1). In general, these results reinforce the notion that babies are capable of accessing prosodic information in general, and rhythmic information in particular. However, not all literature is in agreement on this point. For instance, Christophe and Morton (1998) maintain that two-month old infants born to English-speaking parents are able to discriminate between English and Japanese (stress-timed and mora-timed) but not between French and Japanese (syllable-timed and mora-timed), suggesting that infants are sensitive to the foreignness of a language (i.e. if it is their maternal tongue or not) but not sensitive to the distinction between rhythm classes. However, the authors do not demonstrate that the infants are not exploiting rhythmic cues in the distinction between their maternal language and a foreign language.

While infants can, in theory, be tested for rhythm class discrimination with unaltered utterances, this is not possible with adult participants. Adult participants exploit multiple acoustic cues in language discrimination (phonemic and phonotactic inventory, for instance). In order to remove information not related to syllabic rhythm, utterances have been acoustically altered for use as stimuli in language discrimination tasks.

Sentences filtered at 450 Hz (that is, utterances where all sonic energy below 450 Hz is muted) maintain prosodic features that would contribute to speech rhythm perception, while making it impossible to infer what language is being spoken from the speech signal (Arvaniti and Ross 2012:4). This process, known as low-pass filtering has been exploited in studies of speech rhythm discrimination. For example, Nazzi et al. (1998) showed that French neonates could discriminate between low-pass filtered Japanese and English (respectively a mora-timed language and a stress-timed language) but not between English and Dutch stimuli (two stress-timed languages). This study employed a non-nutritive sucking task (*habituation/ dishabituation* in Christophe and Morton 1998), where the neonates were allowed to suck on a pacifier connected to a pressure transducer; by measuring high amplitude sucking on the pacifier, the author determined that the newborns discriminate languages of different rhythm classes, even if those languages are unknown to the neonates, as was the case with English and Japanese stimuli. However, the infants were unable to discriminate between two stress-timed languages. Referring to the aforementioned study, among others, Nazzi and Ramus state that the fact that children are sensitive to rhythm from a very young age suggests that "infants' acquisition of the metrical segmentation procedure appropriate to the processing of (the rhythmic class of) their native language might rely on an early sensitivity to rhythm." (2003:238).

Ramus and Mehler (1999) apply an alternate method of utterance degradation, known as speech resynthesis. The authors suggest that previous methodologies utilizing low-pass filters preserve some segmental information, and may even corrupt the rhythmic signal by allowing unwanted amplification of certain phonemes, leaving the possibility that the results of Mehler et al. (1988) and Nazzi et al. (1998) may reflect infants' ability

to distinguish intonational differences, rather than rhythmic differences. Ramus and Mehler's speech resynthesis, modeled after the development at IPO at Eidenhoven (as cited in Ramus and Mehler, 1999:515), measures acoustic signals in an utterance, and, using an appropriate algorithm, resynthesizes the spoken material in order to preserve only certain acoustical cues. Ramus and Mehler (1999) applied four transformations (named for the phonemes chosen to resynthesize the speech):

1. "saltanaj": preserves global intonation, syllabic rhythm, and phonotactic structure.
2. "sasasa": preserves global intonation and syllabic rhythm.
3. "aaaa": preserves only global intonation.
4. "flat sasasa": preserves only syllabic rhythm.

This fourth treatment is of specific interest to language-rhythm studies. By replacing all consonants with /s/ and all vowels with /a/, then resynthesizing resulting sentences with a constant fundamental frequency of 230 Hz., the syllabic rhythm is preserved, while all other cues are degraded. When applying the "flat sasasa" treatment, Ramus and Mehler (1999) conclude that subjects could easily discriminate between rhythm classes (in this case English and Japanese, that is, between stress-timed and mora-timed, respectively), showing that rhythm is a robust cue for language discrimination.

Ramus et al. (2000) classify syllable-timed English, stress-timed Spanish, and reportedly intermediately-timed Polish and Catalan (classified as such according the interval measures of duration variability proposed and calculated by Ramus et al. (1999), namely the average standard deviation of vowel duration (ΔV), the average standard

deviation of consonant duration (ΔC), and the percentage of an UTTERANCE comprised of vowel (%V)). The authors applied "sasasa" and "flat sasasa" resynthesis to the languages, and found that participants were able to discriminate English from Spanish, English from Polish, and Spanish from Polish for the conditions retaining only syllabic rhythm (that is "flat sasasa"). Meanwhile, participants were able to distinguish English from Catalan and Polish from Catalan, but not Catalan from Spanish. The authors concluded that Catalan rhythm is similar to that of Spanish, while Polish is neither typologically stress-timed nor syllable-timed, as participants failed to distinguish Polish from both a stress and syllable-timed language (here they rank Catalan as syllable-timed because it was indistinguishable from Spanish). As predicted, Spanish and English were distinguishable.

White, Laurence, Mattys, and Wiget (2012), following Ramus et al. (1999) is using speech resynthesis showed that participants were able to distinguish between languages of different rhythmic categories as well as between two dialects of English. The authors explain this discrimination between two syllable-timed dialects by suggesting that participants use speech rate in distinguishing languages or dialects, but that they are also able to correctly categorize languages when speech rate is normalized, thus demonstrating that participants do distinguish languages with purely duration information. White et al.'s (2012) finding are not in agreement with those of Loukina et al. (2009) who maintain that differences in speech rate alone do not account for perceived differences in speech rhythms. This study shows that speech rate alone cannot distinguish between languages without the inclusion of interval metrics (presumably by participating in an interaction with these IMs). However, as IMs should not greatly differ for two dialects of native

monolingual English (according to traditional rhythm class distinctions, although this is not necessarily empirically proven), it remains difficult to view speech resynthesis as a dependable method of preparing stimuli for speech rhythm discrimination studies.

A consensus regarding the relative merits of low-pass filtering and speech resynthesis in speech rhythm perceptions studies has not been reached. White et al. (2012), following Ramus and Mehler (1999), maintain that "low-pass filtering merely attenuates rather than eliminates segmental information." (2012:666). That is, according to White et al. (2012), low pass utterances still allow listeners to access residual information such as phonemic inventories and phonotactic regularities, for instance. However, other studies continued to use the low-pass filtering methods for perception experiments (i.e. that used by Mehler et al. 1988, mentioned above). One logical reason for this is that low-pass filtered stimuli are more faithful to the original speech signal, while resynthesized stimuli are more heavily altered. Furthermore, various works employing speech resynthesis have come under criticism. For instance, Arvaniti and Ross (2012) criticize Ramus, Dupoux, and Mehler (2003), a perception study using speech resynthesis, as opposed to low-pass filtering, as presenting results incompatible with the idea of rhythms classes.

As mentioned, some authors have defended the previously described speech resynthesis (e.g. Ramus, Dupoux, and Melher 2003; White et al. 2012), while others have maintained that low-pass filtering is preferable in speech rhythm perception studies (see also Nazzi et al. 1998). Neither of these methods of UTTERANCE degradation has been conclusively proven to be superior, although both appear to have certain merits in speech rhythm discrimination studies. However, given the less than reliable results in studies

using speech resynthesis (e.g. Ramus, Dupoux, and Mehler 2003; White et al. 2012) and the fact that the process of speech resynthesis produces a stimulus far more altered than a stimulus produced by low-pass filtering, this dissertation will adopt low-pass filtering in a speech rhythm discrimination study to follow. This will be described in **Chapter 4**.

1.5. Conclusion

The simple fact that speech rhythms have been long described and have been subjected to many attempts to empirically quantify these differences suggests that this linguistic conundrum is worthy of investigation. The existence of rhythmic differences are also supported by studies showing that infants can distinguish between languages of different rhythmic classes (e.g. Nazzi et al. 1998), adults can discriminate between rhythm classes in degraded utterances (e.g. Mehler et al. 1988), and that speech timing appears to be biologically hard wired in a speaker (Wretling and Eriksson 1998).

However, apart from a general consensus that languages do indeed differ rhythmically, the question of how to quantify these rhythmic differences, especially in production, has eluded linguists (e.g. White and Mattys 2007). For these reason this dissertation will experimentally evaluate both the production and perception of speech rhythms across various languages, and incorporate multifactorial analyses and corpus-based frequency effects.

The remainder of this work will be structured as follows: **Chapter 2** discusses two data treatments applied to the speech of monolingual Mexican Spanish speakers and bilingual Californian English/Spanish speakers. Its main purpose is to analyze the PVI as a classifier of speech rhythms. **Chapter 3** discusses a multifactorial analysis of measures

of speech rhythm; it is unique in its statistical approach to speech rhythms and serves to evaluate the efficacy of various IMs, and shed some light on the behavior of bilingual speech rhythms and their relation to the traditional rhythm classes. **Chapter 4** and **Chapter 5** build upon these findings. First, **Chapter 4** conducts a perception-based experiment in order to classify the relative rhythms of utterances of English, Portuguese, and Spanish. Next, **Chapter 5** uses these classifications as the basis for a study of the production of these same utterances, making their relative rhythmic classifications from **Chapter 4** the dependent variable in a multinomial analysis of traditional correlates of speech rhythms. Finally **Chapter 6** presents the conclusions of these studies in the context of their importance to speech rhythms, prosody, phonetics and phonology, and linguistics at large.

Chapter 2

A comparative evaluation of the PVI in speech rhythm discrimination

Overview

As mentioned in the previous chapter, the PVI (pairwise variability index) is often favored by linguists as an apparently transparent and simple method of comparing speech rhythms. However, from a statistical standpoint, it has certain shortcomings (e.g. White and Mattys 2007). In order to evaluate the soundness and efficacy of this metric, the current chapter presents four different methods of evaluating speakers' PVI scores, three based on previous literature, and one more statistically robust evaluation of PVI scores. As all four data treatments are performed upon the same data set, it provides an ideal comparison of the methodologies. The two speaker groups evaluated are bilingual Spanish/English speakers and monolingual Mexican Spanish speakers.

Although most works involving the PVI evaluate the mean of PVI scores for a speaker or utterance, some go on to report a single mean PVI for each speaker type (e.g. Carter 2005). Thus, the first treatment uses the mean PVI score of all the Spanish of monolingual Mexican speakers and the mean PVI of all the bilingual Chicano speakers; this is called the *Speakertype Mean PVI Method*. The second data treatment follows various works (e.g. Grabe and Low 2002; Carter 2005) in evaluating each speakers' mean PVI, and will be referred to as the *Speaker Mean PVI Method*. The third data treatment follows various works (e.g. Low and Grabe 1995; Low, Grabe, and Nolan 2000) in evaluating the mean PVI of each utterance (or *intonation phrases* to use Grabe and Low's (2002) terminology); this will be referred to as the *Utterance Mean PVI Method*. The

fourth data treatment evaluates all PVIs, rather than using a measure of central tendency. That is, each pair of successive vowel durations contributes one PVI score. A binomial logistic regression then evaluates these PVI scores in order to predict the dependent variable, SPEKAERTYPE (*monolingual* or *bilingual*); this method will be referred to as the *Cumulative PVI Method*. After a general introduction, the speaker groups whose unscripted speech is used to evaluate how well these treatments of the PVI differentiate between rhythmic classes are described. The different statistical processes are each described separately and their results are presented and briefly discussed; these discussions touch upon linguistic implications of the data, but methodological implications are more crucial to the current chapter; in fact, as **Chapter 3** evaluates the same speaker groups in a more in-depth manner, linguistic implications are most thoroughly discussed there. To conclude the current chapter, an overall discussion compares and contrasts the four different approaches to speech rhythm evaluation and presents methodological implications. This affords a unique perspective as to the effectiveness of vowel duration interval metrics in the comparison of speech rhythms.

2.1 Introduction

The PVI proves a widely used metric in speech rhythm research. However, it is not without its critics (e.g. Detering 2001). One major criticism, which was mentioned in **Chapter 1**, involves the use of a single mean PVI for an utterance, speaker, or speaker type. In addition to the fact that two PVIs of the same value do not necessarily reflect the same or equivalent series of vowel durations (White and Mattys 2007:519), there are additional shortcomings of the use of the mean of PVI values to evaluate speech rhythms.

One, which is somewhat self-evident, is that it is more statistically viable to consider all the scores for a speaker or speaker type, namely the *Cumulative PVI Method* mentioned above; a binomial logistic regression evaluates all PVI scores rather than relying on a measure of central tendency, such as the mean. Given the availability of computer-aided statistical processing, this method is not only widely available to researchers, but also potentially far more robust in providing a fine-grained perspective of vowel duration variability in naturalistic speech. Thus, the purpose of the current chapter is to compare methods of evaluating PVI scores, considering the use of the mean as a measure of central tendency *(Speakertype Mean PVI Method*, *Speaker Mean PVI Method* and *Utterance Mean PVI Method*) and the use of all the PVI values without a measure of central tendency (*Cumulative PVI Method*); in this manner, this chapter sheds light on the best methodological treatment of the PVI as well as the metric's efficacy. Additionally, it was hoped that these studies would be informative as to the relative position of the Spanish of the two speaker groups on the speech rhythm continuum. These two groups, which will be described in detail below, are monolingual Mexican Spanish speakers and English/Spanish bilingual speakers from California.

2.2. Data

2.2.1. Spontaneous Speech

The studies in this chapter follow Deterding (2001) and Carter's (2005, 2007) methods of recording and analyzing spontaneous speech. Many linguists examine recordings of subjects reading written sentences aloud. This method allows for close control of the material and the avoidance of potential complications, e.g., the presence of diphthongs or

vowel-less syllables, can be controlled for. Furthermore, subjects can be recorded at similar distances from the microphone and can be asked to repeat sentences where pauses or self-correction occurs. However, Deterding (2001) and Carter's various studies of speech rhythm differ in this count. In order to capture more natural speech rhythms, they analyzed recorded spontaneous speech rather than sentences read out loud. Although both spontaneous and scripted speech are still being studied, all other things being equal, natural recorded speech is more likely to reflect spoken language rhythms since "[i]t is well known that there are differences between read and unscripted speech" (Deterding 2001:220). In order to achieve this, the current study uses a small specialized corpus of semi-directed interviews. Subjects were recorded responding to oral questions designed to elicit narrative responses delivered with minimum interruption on the part of the interviewer.

2.2.2. Test Subjects

For this study, two speaker groups were used: ten monolingual Spanish speakers (*Group A*), and ten bilingual English/ Spanish speakers (*Group B*). These groups were chosen for two reasons. First, due to the Mexican heritage of the bilingual speakers, the influence of Mexican Spanish on their bilingual Spanish is especially strong. Second, the geographic proximity of California to Mexico allows for a considerable amount of contact between Mexican Spanish and Californian Chicano Spanish, especially given the number of recent immigrants from Mexico living in California. Thus, both speaker groups share similar linguistic roots in their Spanish, which is traditionally labeled a syllable-timed language, the only difference being that *Group B* also speaks English, a stressed-timed language.

In order to control extraneous variables as much as possible, the study selected test subjects according specific guidelines. Accordingly, the subjects were between the ages of 18 and 25 and currently enrolled in a four-year university at the time of recording, assuring test subjects of a similar age and education level. For each test group, five women and five men were recorded.

The first group, Group A, consisted of ten monolingual Spanish speakers representing speakers of what is traditionally considered a syllable-timed language. In interests of minimizing dialectal variation, subjects in the monolingual Spanish group were all born and raised in a single region of Mexico, in this case the greater Mexico City area and had never lived in a foreign country. The monolingual Spanish speakers were enrolled in a four-year Mexican university, Universidad Nacional Autónoma de México (UNAM) at the time of recording.

The second group, Group B, consisted of ten bilingual English/Spanish speakers. The speakers were second-generation Spanish speakers intended to be representative of the Chicano population in California. Thus, they were born in California to parents who emigrated from Mexico to California during or after their teen years. Second-generation Spanish speakers generally speak Spanish in the home but learn English outside the home, normally through school. This makes them the ideal case studies for bilingualism because they speak both languages from a young age, although they are often dominant in English (e.g. Montrul 2004a, b, 2005). At the time of the study, speakers were enrolled in upper-division Spanish courses at the University of California, Santa Barbara, which means they either took, or tested out of, two years of Spanish instruction at university level plus all their coursework and interaction with instructors is in Spanish.

2.2.3. Hypothesis

Although, the principal purpose of this chapter is to evaluate the PVI, there were some expectations as to the behavior of these two speaker groups. These groups of speakers make for an interesting test case given the opposing classifications of English and Spanish. The monolingual speakers speak what is traditionally regarded as a syllable-timed language whereas the bilingual speakers also speak what is traditionally regarded as a stress-timed language. It is not unreasonable to expect that this contrast will be reflected in the vowel duration variability of the speakers, especially given the results of Carter (2005, 2007) and Fought (2003) who found that Chicano English tends to be more syllable-timed (more similar to Spanish) than American English, and, in the case of Carter, African American English. Thus, it was expected that Chicano Spanish would be more stress-timed than that of their monolingual counterparts (e.g. MacLeod and Stoel Gammon 2005 for similar findings for voice-onset times in Canadian English and French).

2.2.4. Data Logging

Vowel duration was recorded for each phrase according to accepted methodology, as described by White and Mattys (2001) for determining the onset and offset of the vocalic nucleus. Accordingly, a visual inspection of speech waveforms and wideband spectrograms using PRAAT phonetic software (Boersma and Weenink 2010) was carried out in order to determine and mark the onset and offset of vowels and measure their durations. The current study calculated a PVI according to the aforementioned equation,

resulting in a series of PVIs for each test subject. Starting at the beginning of the recording, sentences or phrases displaying a minimal interruption or interference were selected and examined in order to record a minimum of 50 data points per speaker. Once these 50 data points were extracted, vowel durations were recorded until the end of the current sentence or phrase. As in Carter (2007), for both English and Spanish, the syllable directly before a pause (as would be denoted by a period, comma, etc.) or hesitation marker, restart, or repair was eliminated due to common elongation of the pre-pausal syllable. The calculation of PVIs and all statistical analysis of data were completed using R software for statistical computing and graphics (R Development Core Team, 2013)[2].

2.2.5. Treatment of special cases

Given the spontaneous nature of the speech, unnatural syllable elongations due to speaker confusion were eliminated. Regarding Spanish diphthongs, the methodology employed by Carter (2007) was adopted. Specifically, Spanish diphthongs not marked by orthographic accents will be considered as a single vowel. English canonical diphthongs /ai/, /oi/ and /aw/ are also measured as a single vowel. In instances of specific individual complications, such as syllable deletion, these were addressed on a case-by-case basis.

2.3. Speakertype Mean PVI

2.3.1. Statistical Evaluation: Speakertype Mean PVI

As mentioned, studies employing the PVI for speech rhythm distinction tend to discriminate between using the mean of a speaker's PVI scores or the mean of the PVI

[2] I wish to thank Prof. Stefan Th. Gries of UCSB for writing the R function to calculate the PVI values.

scores for each utterance; however, some go on to report a single mean PVI score for each speaker type. It is unclear from the literature just how these means are calculated. Taking Carter (2005) as an example, both overall speaker type PVI means are reported, as well as mean PVI scores for each speaker. It is possible that these speaker type mean PVI scores are based upon each speaker's mean PVI score, as in Figure 2.1.

Speakertype *X*:
Mean PVI- Speaker$_1$: Mean(PVI$_1$, PVI$_2$, …, PVI$_n$) Mean PVI- Speaker$_2$: Mean(PVI$_1$, PVI$_2$, …, PVI$_n$) Mean PVI- Speaker$_n$: Mean(PVI$_1$, PVI$_2$, …, PVI$_n$)
Speakertype *X* PVI Score: Mean(Mean PVI- Speaker$_1$, Mean PVI- Speaker$_2$… Mean PVI- Speaker$_n$)

Figure 2.1: Possible method of calculation for Speakertype Mean PVI score.

However, it is also possible that Carter (2005) calculated the mean PVIs as in in Figure 2.2. This chapter will use the more statistically sound option ("statistically more sound" in that it loses less information). The method above involves taking the 'mean of a mean', but the current chapter avoids this by calculating the Speakertype Mean PVI as below.

Speakertype *X*: Mean(Speaker$_1$: PVI$_1$, PVI$_2$, …, PVI$_n$ + Speaker$_2$: PVI$_1$, PVI$_2$, …, PVI$_n$... + Speaker$_n$: PVI$_1$, PVI$_2$, …, PVI$_n$)

Figure 2.2: Speakertype Mean PVI score as calculated in the current chapter.

2.3.2. Results: Speakertype Mean PVI

As previously mentioned, the expectation for this data set was that the bilingual Chicano speakers would show more vowel duration variability as compared to the monolingual speakers due to their dominance in a stressed time language. Thus, it was expected that the Chicano speakers would have higher PVI scores than the monolingual participants.

However, the results of the *Speaker Mean PVI* analysis did not reflect the original hypothesis. In fact, the mean PVI of Mexican speakers were higher than that of the bilingual Californian speakers. The mean PVI of the Mexican subjects was 0.44 (95% confidence interval= 0.412 : 0.468; sd=0.324) while the mean PVI of the bilingual Californian speakers was 0.361 (95% confidence interval= 0.338 : 0.383; sd=0.262). According to a Wilcoxon rank sum test, this difference in means is highly significant: $W = 114118$, $p < 0.001$ (see Figure 2.3).

2.3.3. Discussion: Speakertype Mean PVI

The fact that the data do not reflect the original hypothesis provides several points of interest for discussion. The fact that native Spanish speakers show more variation in vowel duration than their bilingual counterparts may well be related to the monolingual speakers' dominance of the language.

This will be discussed more in detail following the results of **Chapter 3**, as these results are better contextualized in consideration of some methodological implications of the calculation of the PVI and its use as a classifier of speech rhythms. A more relevant point to consider here is the viability of these conclusions given the methodology applied. While it is current practice in some speech rhythm literature to present and discuss the mean PVIs for each speaker type (e.g. Carter 2005), this is statistically problematic. Not only does the use of the means 'wash away' much information from the data, but PVIs appear to not be normally-distributed, at least in the current data, making the mean an unreliable measure of central tendency; according to a Shapiro-Wilk test of normality, the PVI values from which the means are calculated are not normally distributed (W =

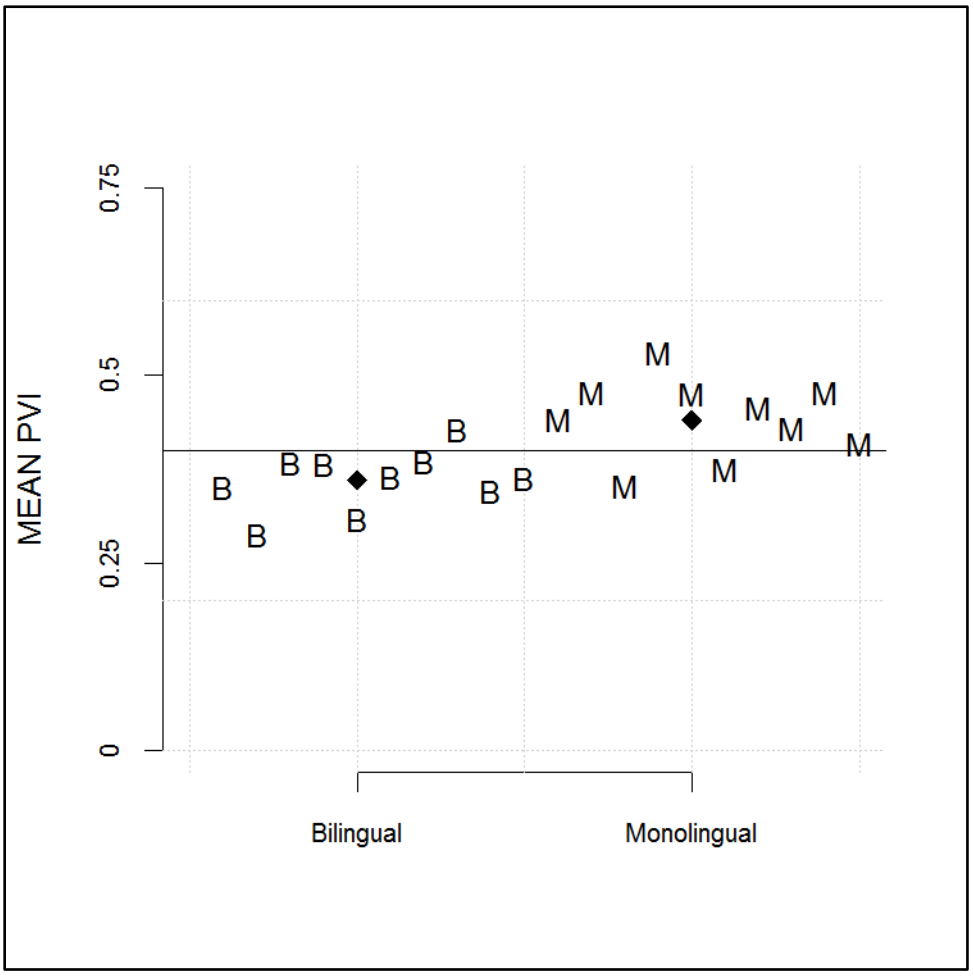

Figure 2.3: The mean PVIs for each speaker, grouped according to speaker type; the Bs are bilingual participants and the Ms are monolingual participants. The black diamonds represent the mean for each speaker type and the horizontal line represents the mean PVI for all speakers.

0.9323, p < .0001). Each speaker type's PVI values also deviate from normality (SPEAKERTYPE= *bilingual* W= 0.9366, p < .0001; SPEAKERTYPE= *monolingual* W = 0.9354, p < .0001). While it would a possibility to use a different measure of central tendency, such as the median (as in Carter 2007) or a weighted mean, it is still the case that there is a great deal of variation in the distribution of the PVI values, suggesting that any measure of central tendency would remove a great amount of information about rhythmic variation within speaker types (and within speakers, see below). However, in order to contextualize the methodology applied in previous literature, the next two

sections evaluate the mean PVI for each speaker (e.g. Grabe and Low 2002) and the mean PVI for each utterance (e.g. Low and Grabe 1995).

2.4. Speaker Mean PVI

2.4.1. Statistical Evaluation: Speaker Mean PVI

The data evaluation in the current section followed Carter (2005) and Grabe and Low (2002) in calculating a mean PVI for each speaker, rather than for each utterance (as in Low and Grabe 1995, for example). Each speaker's mean PVI was calculated as the mean of all of their PVI scores (as opposed to basing them on the mean of each utterance). Observed mean PVI values are plotted above on Figure 2.3. While previous studies using *Speaker Mean PVI* scores simply report the means (and perhaps a mean for each speaker type as well), the current chapter used a more statistically advanced technique in order to better evaluate the utility of this metric in speech rhythm discrimination studies. Thus, a binary logistic regression was generated to predict SPEAKERTYPE (*bilingual* or *monolingual*) according the SPEAKER MEAN PVI scores.

2.4.2. Results: Speaker Mean PVI

The predictor SPEAKER MEAN PVI was highly significant in predicting SPEAKERTYPE ($p=.02$, $R^2=.60$). The resulting model was able to accurately classify bilingual versus monolingual speakers 85% of the time, which is highly significantly better than a model that predicts the most frequent level of SPEAKERTYPE 100% of the time ($p<.001$)[3]. The same trend that was present in the previous section, namely that

[3] It should be noted that each speaker type was represented 50% in the data, so this model would be correct

monolingual speakers displayed higher PVI values than bilingual speakers on a whole was also present in the current analysis (see Figure 2.4[4]).

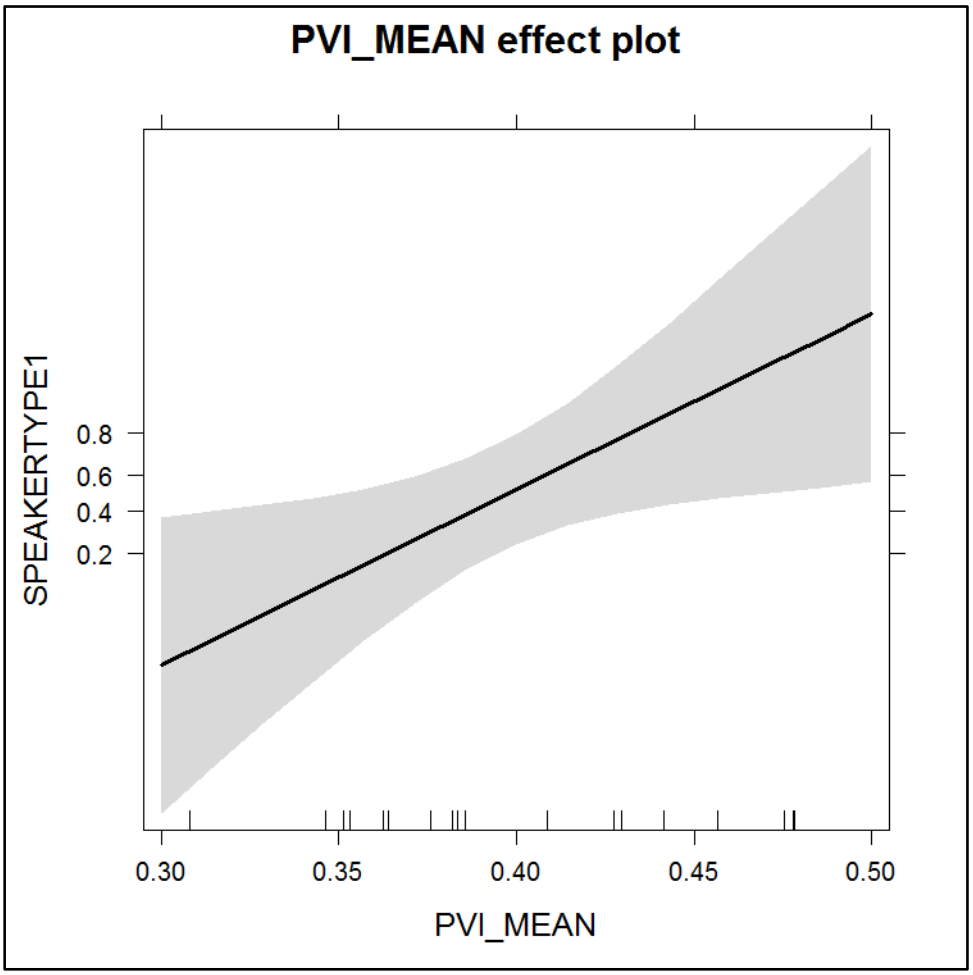

Figure 2.4: Predictions for SPEAKERTYPE according to the mean PVI for each speaker. The mean PVI scores are represented on the horizontal axis, with higher mean PVI scores to the right hand side of the graph. The prediction for SPEAKERTYPE is represented on the vertical axis, with those values above 0.5 being predicted *monolingual*.

half of the time.

[4] Figures 2.4, 2.6, and 2.8 were generated using the effects package (Fox 2014) for R (R Development Core Team 2013)

2.4.3. Discussion: Speaker Mean PVI

Although the current model is efficient at predicting SPEAKERTYPE according the mean PVI for each speaker, this is not to say that it is a useful model to accurately understand speech rhythms. Once again, the use of the mean is very problematic in washing away a great amount of variation within each speaker that would be otherwise visible. Furthermore, as mentioned above, the fact that the data from which these means are derived is not normally distributed proves to be a serious issue when considering the reliability of this model. According to a Shapiro Wilk test of normality, only four out of the twenty speakers had normally distributed PVI values. Given that the data are not normally distributed, these Speaker Mean PVI scores cannot be said to accurately reflect the central tendency of the speakers.

2.5. Utterance Mean PVI

2.5.1. Statistical Evaluation: Utterance Mean PVI

The data evaluation in the current section is very similar to that of *Section 2.4* with the exception that mean PVI scores were recorded for each utterance (or intonation unit), rather than for each speaker, as in Low and Grabe (1995), for instance. This theoretically affords a more fine-grained perspective as compared to the use of the *Speaker Mean PVI Method*, as within-speaker variation is visible. As in the previous section, a binary logistical regression was generated to predict SPEAKERTYPE (*bilingual* or *monolingual*), this time with MEAN UTTERANCE PVI. The mean PVI values are plotted below in Figure 2.5.

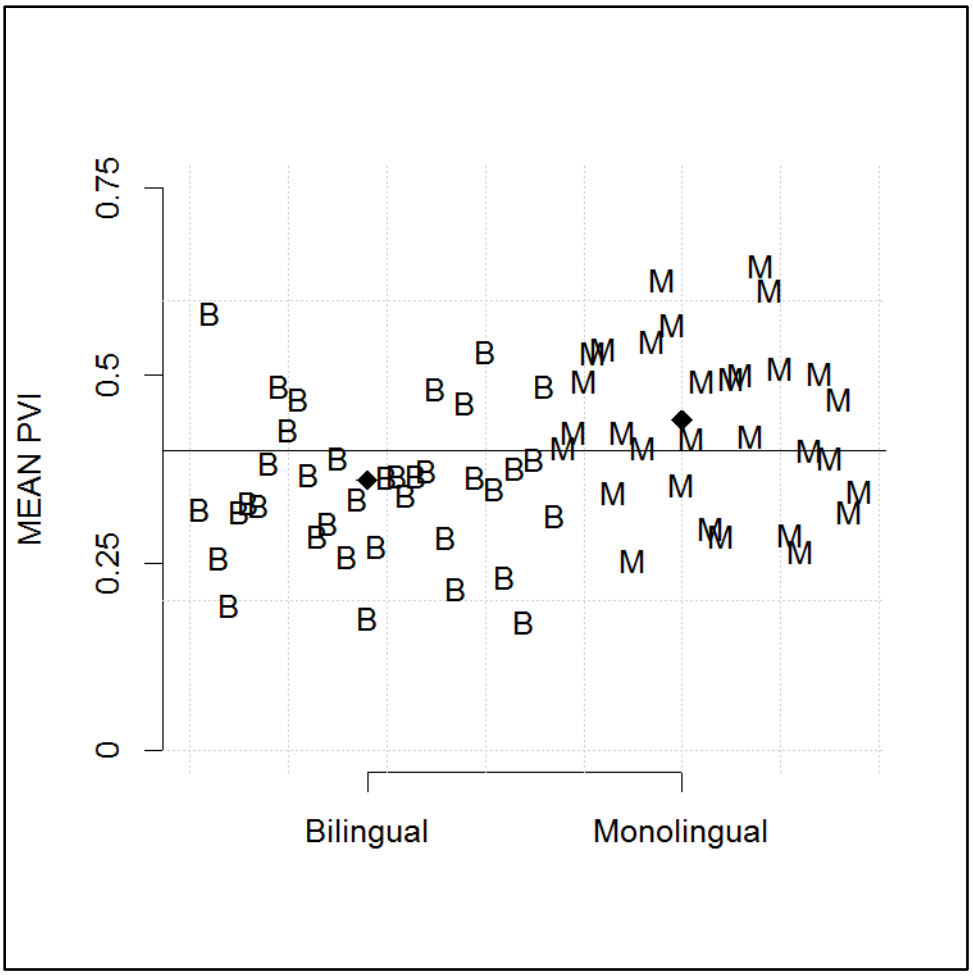

Figure 2.5: The mean PVIs for each utterance, grouped according to speaker type; the Bs are bilingual participants and the Ms are monolingual participants. The black diamonds represent the mean for each speaker type and the horizontal line represents the mean PVI for all speakers.

2.5.2. Results: Utterance Mean PVI

The predictor UTTERANCE MEAN PVI was highly significant in predicting SPEAKERTYPE ($p<.001$, $R^2=.20$). Once again, the monolingual speakers displayed higher PVI values than bilingual speakers on a whole (see Figure 2.6). However, what is more informative is that the present model was far less accurate in predicting SPEAKERTYPE, as compared to the *Speaker Mean PVI Method*. The R^2 value has

dropped from .60 in the previous model to .20 here, indicating that far less variation in the model is explained by the dependent variable. Furthermore, the C score has dropped to .73, below the threshold of .80 for an accurate model. The current model was able to accurately classify bilingual versus monolingual speakers 69% of the time. While this still performs significantly better than a model that predicts the most frequent level of SPEAKERTYPE 100% of the time ($p<.01$), this model performs much worse than the model based on just SPEAKER MEAN PVI scores. It is noteworthy that in the case of the *Utterance Mean PVI Method*, it is in fact more statistically viable to consider the mean as a measure of central tendency. A Shapiro Wilk test for normal distribution revealed that the distribution of the PVIs was normal for 52 out of 67 utterances tested; one utterance was too short to perform this test on. However, despite the increased reliability as the mean utterance PVI as a measure of central tendency, the model performs worse than the *Speaker Mean PVI Method*.

2.5.3. Discussion: Utterance Mean PVI

It is troubling that the model that contains more information (that is the *Utterance Mean PVI* model contains 68 data points, as compared to 20 in the *Speaker Mean PVI* model), and uses a measure of central tendency that can be considered more reliable, is less accurate in correctly classifying the dependent variable, SPEAKERTYPE. This is not indicative of the strength of the *Speaker Mean PVI Method* model; rather, it indicates that taking the mean of each speaker is removing a good deal of within-speaker variation that should be considered in speech rhythm discrimination analysis. Unlike the previous analyses, the non-normal distribution of the PVI values is not a serious concern for the

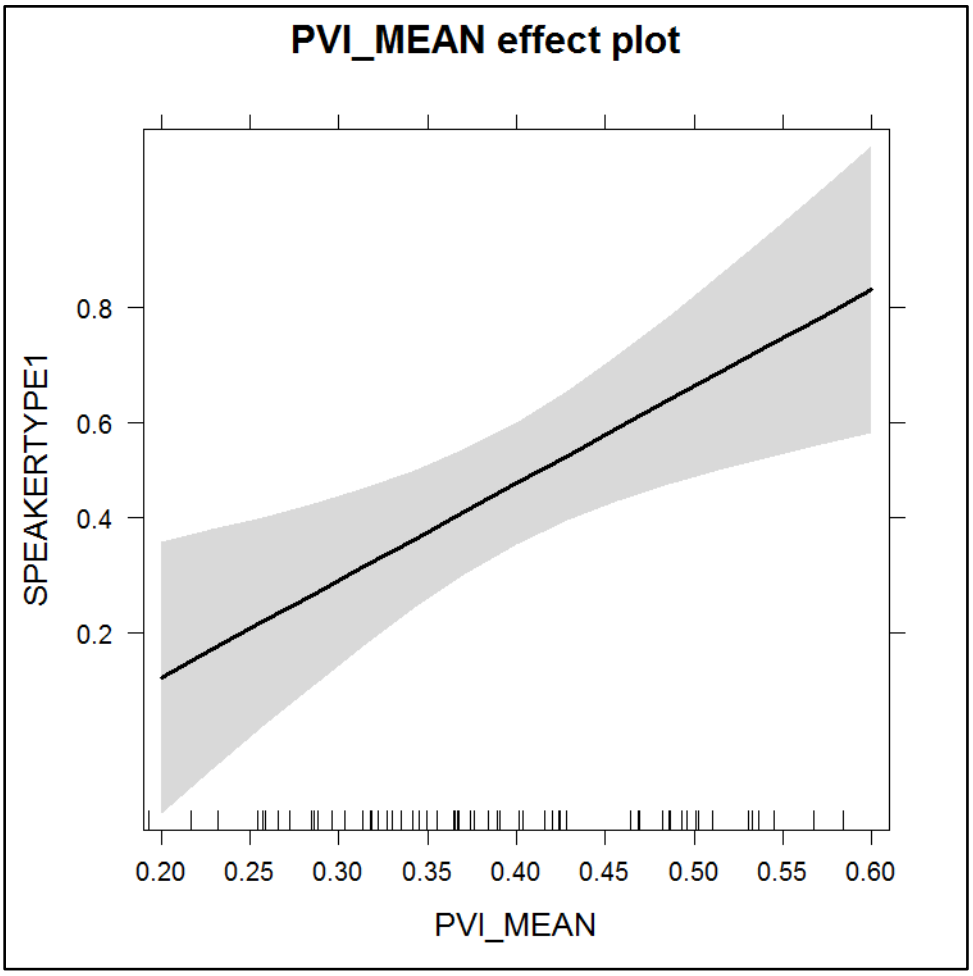

Figure 2.6: Predictions for SPEAKERTYPE according to the mean PVI for each utterance. The mean PVI scores are represented on the horizontal axis, with higher mean PVI scores to the right hand side of the graph. The prediction for SPEAKERTYPE is represented on the vertical axis, with those values above 0.5 being predicted *monolingual*.

use of the mean. However, the model performance suggests the the *Utterance Mean PVI Method* fails to discriminate reliably between the two speaker groups. In an attempt of a more robust analysis, the following analysis will not use the mean to evaluate the PVI scores, but instead consider all PVI values in the evaluation of the speech rhythms of monolingual Mexican speaker and bilingual Chicano speakers.

2.6. Cumulative PVI

2.6.1 Statistical Evaluation: Cumulative PVI

As mentioned, the statistical evaluation of the *Cumulative PVI* differs from the previous methodologies in that, rather than considering the various means of each utterance, speaker, and/or speaker type, it uses all individual PVI values (that is, for each pair of successive vowel durations) in a regression analysis. As in *Sections 2.3* and *2.4*, a binary logistic regression was created to predict SPEAKERTYPE, but this time according to all speaker's PVI scores. The observed PVI scores are plotted below on Figure 2.7.

2.6.2. Results: Cumulative PVI

After considering all 1019 data points, PVI was a significant predictor of speaker type (that is, *monolingual* vs. *bilingual* speakers; $p<.0001$); however, the resulting model had extremely low classificatory power ($R^2=.02$). The C score has once again dropped from the previous model to 0.56. The model is able to to correctly identify SPEAKERTYPE, 55% of the time. While the results of this statistical exploration reflect the same trend as those of the previous models, namely that monolingual speakers display higher vowel duration variability than their bilingual counterparts (see Figure 2.8), the low classificatory power of the model is far more noteworthy. Once again, a model that contains more data points, and thus more information about the vowel duration variability between speaker types is less accurate than one with fewer data points.

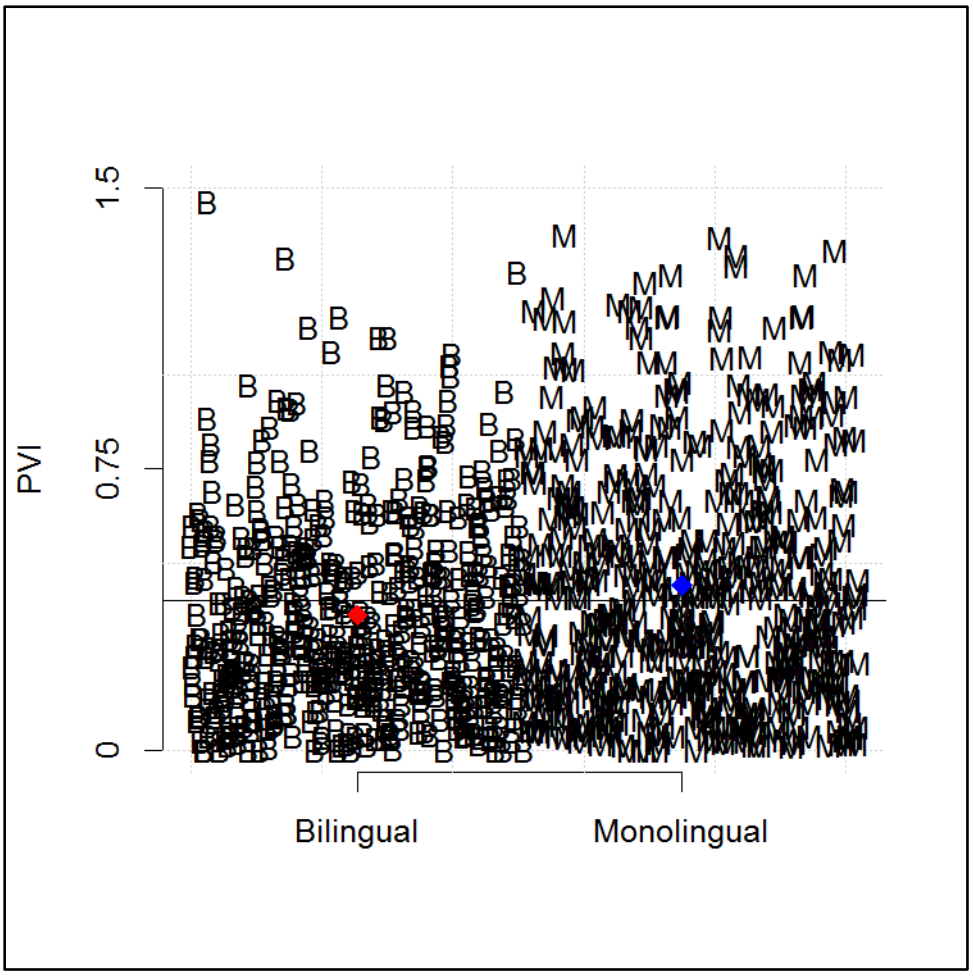

Figure 2.7: All observed PVI scores, grouped according to speaker type; the Bs are bilingual participants and the Ms are monolingual participants. The red diamond represents the mean for bilingual speakers, the blue diamond represents the mean for monolingual speakers, and the horizontal line represents the mean PVI for all speakers.

2.6.3 Discussion: Cumulative PVI

As mentioned, the trend reflected by the *Cumulative PVI Method* is the same as that reflected by the two methodologies considering the means of PVI values. Overall, the Monolingual Mexican speakers show more vowel duration variability as compared to the Bilingual speakers. The fact that native Spanish speakers show more variation in vowel duration than their bilingual counterparts may be related to the monolingual speakers' dominance of the language. Their aptitude in the use of the language as well as the ability

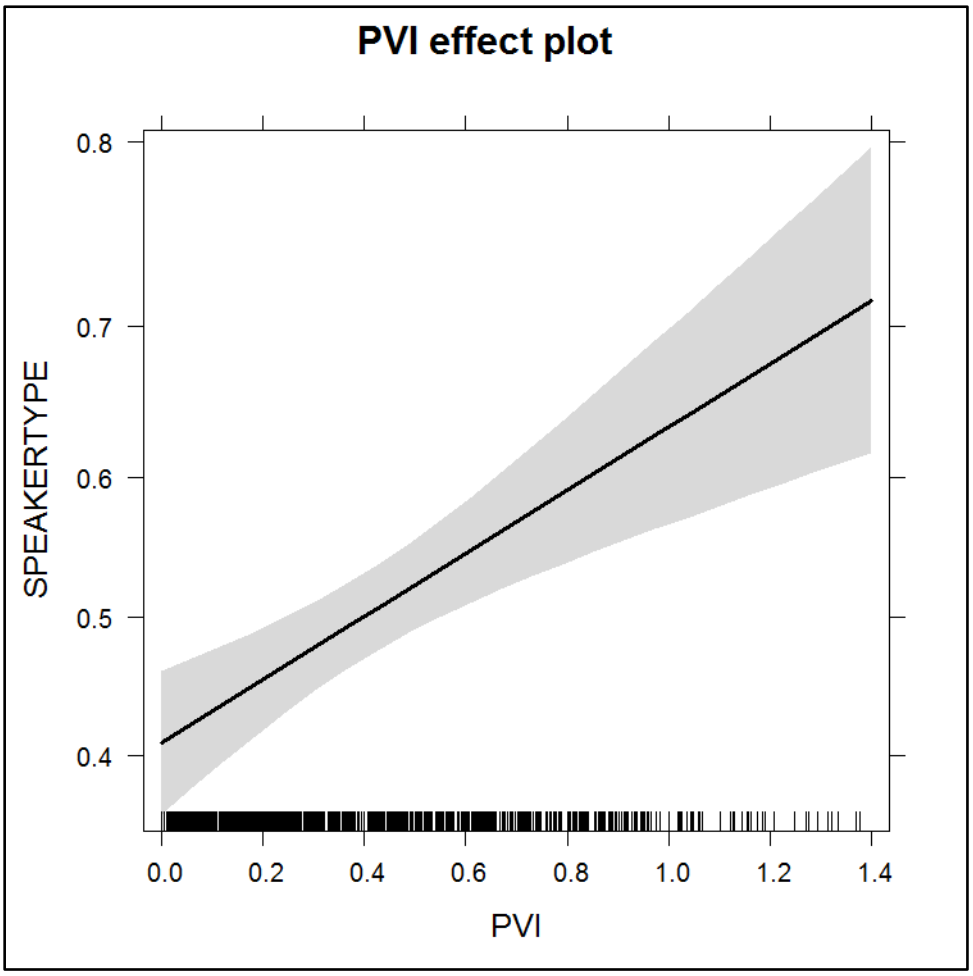

Figure 2.8: Predictions for SPEAKERTYPE according to PVI. The PVI scores are represented on the horizontal axis, with higher mean PVI scores to the right hand side of the graph. The prediction for SPEAKERTYPE is represented on the vertical axis, with those values above 0.5 being predicted monolingual.

to employ language across a variety of registers may allow them to employ more variation in rhythms, leading to a higher PVI. These results are in agreement recent studies on speech rhythm. Benton, Dockendorf, Jin, Liu, Edmondson concluded that rhythm varies between speakers, and "in some cases across genres" (2007:1272). Furthermore, it is difficult to establish rhythmic typologies for an entire language based on a single dialect. This is exemplified by a difference in rhythms between Californian Chicano Spanish and Mexican Spanish in Mexico City. Despite the geographical proximity of California and

Mexico, the data seems to reflect that the dialects are typologically different. It is accepted that different varieties of Spanish may have different vowel systems. So, while it is accepted that intonation defines different varieties, it may be that vowel systems of differing varieties of Spanish are also marked by rhythmic variety.

However, once again, the fact that more information is associated with a less accurate classification accuracy is the most central point of import to the current chapter. Furthermore, the current analysis does not use a measure of central tendency, so the non-normal distribution of the data is not an issue. Even without this factor, the model does not perform well in identifying the dependent variable. This indicates that the use of the mean of PVI scores (whether for speaker type, speaker, or utterance) not only removes a great deal of relevant information (inter-speaker type, inter-utterance, and inter-speaker variation) to the study of speech rhythms, but that it does so in a risky manner, due to the non-normal distribution of the PVI values. This conclusion will be further discussed in the following section.

2.7. Methodological Implications

After examining the statistical process employed leading to the results discussed in the current chapter, it is clear that two issues needed to be addressed. At the risk of repetition, this section will briefly review these two issues in order to better contextualize the results for the current chapter, The first regards the reporting a mean PVI speaker for speaker or speaker type, as seen in the first three. Reporting means as measures of central tendency assumes that the data is (nearly) normally distributed. In the reporting of mean PVI values, no proof (to the author's knowledge) is given in previous speech rhythm literature

that PVI values are normally distributed when mean PVIs are reported. In the case of the current data, in fact, the speaker mean PVIs deviate from a normal distribution, which indicates that the mean is not a reliable measure of central tendency for PVI values. Alternate measures of central tendency that do not require normally distributed data (for example, the median or a weighted mean) would be potential alternate measures that could be used, but as the remainder of this paragraph will show, this is not the best choice in evaluating the data. This is due to the fact that it is possible to consider all PVI values, as in the *Cumulative PVI Method.* This is a more statistically robust method of evaluating the data, as no information is removed by the use of a measure of central tendency. However, when this evaluation is performed, the resulting model is not reliable in classifying SPEAKERTYPE. This leads to the second issue regarding the PVI as a metric of speech rhythms, discussed in the paragraph below.

A very important consideration of the analyses in the data is that as each model increases in terms of the number of data points it considers, it also becomes far less accurate in classifying the dependent variable. The *Speaker Mean PVI Method* evaluated 20 data points and was able to correctly classify SPEAKERTYPE 85% of the time; the *Utterance Mean PVI Method* evaluated 68 data points and achieved 69% classification accuracy (although the use of the mean as a measure of central tendency was appropriate in this case); the *Cumulative PVI Method* considered 1019 data points and was accurate only 55% of the time, which is scarcely better than chance. In this final case, due to the 1018 degrees of freedom, PVI is significant as a predictor of SPEAKERTYPE ($p<.001$), but the model can only account for about 2% of the variation in the PVIs values, which is

to say that it is not particularly effective in assessing the difference in PVI values between speaker types at all.

The fact that the PVI only works as an accurate classifier of SPEAKERTYPE when the mean PVI of each speaker type or speaker is considered is very telling; the variation of PVI values for each speaker is nearly as varied as the difference in PVIs between speakers. The result of this is that only upon 'evening out' this variation with a (unreliable) measure of central tendency do the differences between monolingual and bilingual speakers become evident.

Given that the PVI is ineffective in distinguishing between two dialects of Spanish, it is apparent that it is necessary to assess these complex data in a more thorough manner. A multifactorial regression is beneficial in two manners. First, it allows the inclusion of additional potentially relevant variables, such as other interval metrics (e.g. Ramus, Nespor, and Mehler's (1999) various IMs) and corpus-based frequency measures. Secondly, a multifactorial approach allows potential interactions between the variables, affording a much more complete analysis of the behavior of this data set. In this way it is possible to not only understand the differences in the speech rhythms of the two speaker groups, but also to understand the efficacy of the various rhythm metrics. This is particularly important given the lack of consensus of the best IMs for the evaluation of speech rhythms; in fact, it is not accepted that any one IM is useful in speech rhythm evaluation (e.g. Loukina et. al 2009). The following chapter will reevaluate the same data set from the current chapter. However, it will apply a multifactorial approach with the goal of 1) comparing the speech rhythm of monolingual Mexican Spanish and bilingual

Chicano Spanish, and 2) evaluating the efficacy of various IMs for the comparison of speech rhythms. The results of this methodology are discussed in the following chapter.

2.8. Interim Summary

Before proceeding with the remainder of this dissertation, this section will briefly summarize the previous two chapters in order to remind the reader of the current state of speech rhythm research and why the methodologies of the following chapters are necessary.

As the first chapter states, several factors suggest the existence of speech rhythms, including widespread perception (Loukina, Kochanski, Rosner, and Keane 2011) and speech rhythm discrimination by infants (e.g. Nazzi, Bertoncini, and Mehler 1998). However, while the existence of speech rhythms is not controversial, no single empirical proof of rhythmic differences between different languages or dialects has been universally accepted. Two major approaches have been adopted in attempts to quantify speech rhythms: production and perception studies. In the latter case, the ability of adults to distinguish between languages of different rhythm classes on the basis of a speech signal that has been altered to include only syllabic rhythm (e.g. Ramus and Mehler 1999) or the ability of infants to distinguish between languages of a different rhythm class (on the basis of an altered or unaltered speech signal, e.g. Nazzi, Jusczyk, and Johnson 2000) have been given as proof of the existence of speech rhythms. Production studies, meanwhile, attempt to use interval metrics based upon the measurement of segments of the speech signal to quantify rhythmic differences between languages or dialects. These IMs are generally intended to quantify the variability of segment durations, with the

general notion that higher segment duration variability is present in stress-timed languages, while syllable-timed languages have more regular segment durations. The current chapter investigated the PVI (e.g. Low and Grabe 1995), one of the most widely used IMs in speech rhythm research and identified several practical shortcomings of this metric. Due to these shortcomings, **Chapter 3** will reevaluate the PVI as well as several other traditional IMs in distinguishing between utterances of monolingual Mexican Spanish and bilingual Chicano Spanish. Following this thorough multifactorial analysis, **Chapter 4** uses a perception study of utterances of English, Portuguese, and Spanish in order to determine if these utterances truly differ from one another in terms of rhythmic perception. The results of this chapter then lead to the analysis of **Chapter 5**, which explores what acoustic properties of these same utterances prompt perceived differences in rhythm. Finally, the implications of this dissertation are discussed in **Chapter 6**.

Chapter 3

A comparison of measures of speech rhythm in Mexican and Chicano Spanish speakers

Overview

This chapter considers the same data used in **Chapter 2**, evaluating the rhythmic differences between monolingual Mexican Spanish and bilingual Chicano Spanish. However, this chapter differs in several counts from the analyses presented in the previous chapter. Rather than employing the *Mean PVI Method* or the *Raw PVI Method*, the chapter uses more advanced methodology in presenting a multifactorial analysis. Furthermore, rather than only consider the PVI as a metric for distinguishing differing rhythmic classes, it also considers other IMs. Specifically, it includes IMs as suggested by Deterding (2001) as well as corpus-based measures of frequency. The remainder of this chapter will introduce the subject and review the data and methods used (although as the data are the same as the previous chapter, this description will be brief). The statistical methodology is discussed and the results follow. A discussion covers the linguistic and methodological implications of these results, affording a unique perspective as to the effectiveness of vowel duration interval metrics in the comparison of speech rhythms, as well as the importance of corpus-based frequency measures to the study of speech rhythms. Finally, the implications of these findings are presented, and explain how these results prompt the further investigation in the study of speech rhythms described in this dissertation.

3.1. Introduction

The statistical evaluation performed in the current chapter was undertaken as a direct result of the results described in Chapter 2. Both of the methods of calculating speaker PVI scores described in the previous chapter prove inconclusive as to the rhythmic nature of Monolingual Mexican Spanish as compared to Bilingual Chicano Spanish. Furthermore, these results also shed doubt on the utility of the PVI as a metric of speech rhythms. Thus, the current chapter seeks to a) compare the speech rhythms of these two speaker groups and b) explore more reliable metrics of speech rhythm classification. It also evaluates the variation of speech rhythms (or at least vowel duration variability) according to corpus-based frequencies, a novel approach in speech rhythm research[5]. It has been shown that certain aspects of pronunciation vary with word frequency (e.g. Bell et al. 2009; Raymond and Brown 2012); it is not unreasonable to expect that speech rhythms may do the same.

3.2. Data

The data used in the current chapter is the same data from Chapter 2; thus the discussion is limited to a quick review of the nature of the data. The data is spontaneous speech culled from a specialized corpus of semi-directed interviews. The two speaker groups are each comprised of 5 women and 5 men. The two test groups were used: ten monolingual Spanish speakers (*Group A*), and ten bilingual English/ Spanish speakers (*Group B*). As mentioned, the subjects were between the ages of 18 and 25 and currently enrolled in a

[5] The multifactorial statistical evaluation described in this chapter is from Harris and Gries (2011). I am grateful to Prof. Stefan Th. Gries for performing that statistical exploration and generating graphical representations.

four-year university assuring test subjects of a similar age and education level. For each test group, five women and five men were recorded.

3.2.1. Hypothesis

Recall that the monolingual speakers speak a syllable-timed language while the bilingual speakers also speak a stress-timed language (at least according to a traditional rhythm class distinctions). In **Chapter 2** it was expected that Chicano Spanish would be more stress-timed than that of their monolingual counterparts due to their dominance in English, a stress-timed language. However, the results of **Chapter 2** ultimately indicate the opposite trend; Chicano speakers show less variation in terms of vowel duration as compared to Mexican speakers, so they have what would be regarded as a less stress timed Spanish as compared to their monolingual counterparts. While, these results cannot be considered definitive due to the shortcomings of the PVI metric (see **Chapter 2**), this trend is reflected in all data evaluations. For this reason the expectations of the current chapter were different than the original hypothesis; it was expected that the trend identified in **Chapter 2** would be preserved in the current data evaluation as, with Monolingual Mexican speakers showing more variability in terms of vowel duration as compared to the Spanish of bilingual Chicano Spanish speakers.

3.2.2. Data Logging

The same data was used in the current chapter as that in Chapter 2, thus the data logging and treatment of special cases was identical. One way in which the current chapter differs from the previous one is that the pre-pausal syllable of each Intonational Unit was

included as a data point. In previous studies, this syllable was eliminated from the data due to pre-pausal lengthening (e.g. Low and Grabe 1995). In the case of the current data, the inclusion of the variable SYLLABLE, which gives the position of the syllable in the phrase, allows an analysis of the actual behavior of this last (usually elongated) syllable of the phrase as it relates to the dependent variable SPEAKERTYPE.

3.3. Multifactorial Analysis

3.3.1. Statistical Evaluation: Multifactorial Analysis of Interval Measures

To prepare the data for statistical analysis, each syllable in the data was annotated for a number of variables. The dependent variable is SPEAKERTYPE, a categorical variable with two levels, *monolingual* vs. *bilingual*; the following is the list of independent variables (note that several variables that had been suggested as metrics of speech rhythms were included (e.g. White and Mattys 2007)):

- SPEAKERSEX: a categorical variable with two levels, *male* vs. *female*;
- IU: a numeric variable ranging from 1 to *n*, where *n* is the number of IUs (intonation units; e.g. Du Bois 1991) per speaker; this is included to rule out within-speaker changes over the course of the interview;
- DURATION: a numeric variable providing the length of the vowel in ms;
- SYLLABLE: a numeric variable representing the position of the syllable in the IU; this is included as a control covariate to make sure that changes over the course of an IU would be controlled for;

- TOKENFREQ: the log of the frequency of the word form in which the vowel occurred in the Corpus del Español;
- LEMMAFREQ: the log of the frequency of the lemma in which the vowel occurred in the Corpus del Español;
- PVI: the PVI of the duration of the current and the next syllable within the IU (if there was one), computed as in (1);
- SD and SDLOG: the standard deviation of the duration of the current and the next vowel within the IU (if there was one) and its natural log (after addition of 1 to cope with 0s)[6];
- VARCOEFF and VARCOEFFLOG: the variation coefficient of the duration of the current and the next vowel within the IU (if there was one), as computed in and its natural log (after addition of 1 to cope with 0s), computed as in (2).

$$(1) PVI = \frac{|(vowelduration_1 - vowelduration_2)|}{mean(vowelduration_1, vowelduration_2)}$$

$$(2) VARCOEFF = sd\frac{(vowelduration_1, vowelduration_2)}{mean(vowelduration_1, vowelduration_2)}$$

To determine how well these these variables and their interactions distinguish between the monolingual and the bilingual speakers, all 1061 complete data points were entered into an automatic stepwise bidirectional logistic regression model selection process, trying to predict SPEAKERTYPE: *monolingual*. Using the stepAIC function of

[6] It is worth noting that this metric differs from the metric suggested by Ramus, Nespor, and Mehler (1999), who used the average standard deviation of vowel durations of a phrase, rather than the pairwise measurement employed here.

the R package MASS (e.g. Ripley 2011 and R Development Core Team 2013, predictors – variables and interactions between them – were added or subtracted until a optimal model was reached, in the sense that it did not benefit from the addition or subtraction of another predictor. As mentioned above, unlike in the *Mean PVI Method* and the *Raw PVI Method*, the pre-pausal syllable of each Intonational Unit was included as a data.

3.3.2. Results: Multifactorial Analysis of Interval Measures

As a result of the model selection process, several predictors were omitted because they did not contribute enough classificatory power to the model (e.g., IU and TOKEN FREQ). The overall fit of the final regression model to the data is significant (log-likelihood=150.22; df=12; $p<0.001$), but the classification accuracy is only intermediately good (C=0.704; R^2=0.176; classification accuracy=64.7%); Table 1 provides the coefficients of the final model.

Predictor	Coefficient	*p*	Predictor	Coefficient	*p*
DURATION	-0.02	0.046	DURATION: SYLLABLE	≈-0.001	0.036
SYLLABLE	0.13	<0.001	DURATION: SDLOG	0.006	0.005
SD	-0.04	<0.001	PVI : LEMMAFREQ	0.56	0.001
VARCOEFFLOG	0.47	<0.001	SDLOG: LEMMAFREQ	-0.12	0.017

Table 3.1: Significant predictors in the final logistic regression model

As shown in Table 3.1, there are two main significant main effects and several significant interactions. Such a complex data set warrants a thorough examination; for an exhaustive discussion of these effects, see Harris and Gries (2011). However, the current chapter will

only discuss the relevant methodological implications of certain interactions upon the study of speech rhythms.

3.3.2.1. Main Effects

Figure 3.1 shows the main effects of SD and VARCOEFFLOG on the predicted probability of monolingual: As the variability of two vowels increases in terms of SD, the prediction is becoming more likely to be bilingual. However, as the variability of two vowels increases in terms of VARCOEFFLOG – i.e., the measure of dispersion less affected by the mean duration – the prediction is becoming more likely to be monolingual, at least on the whole.

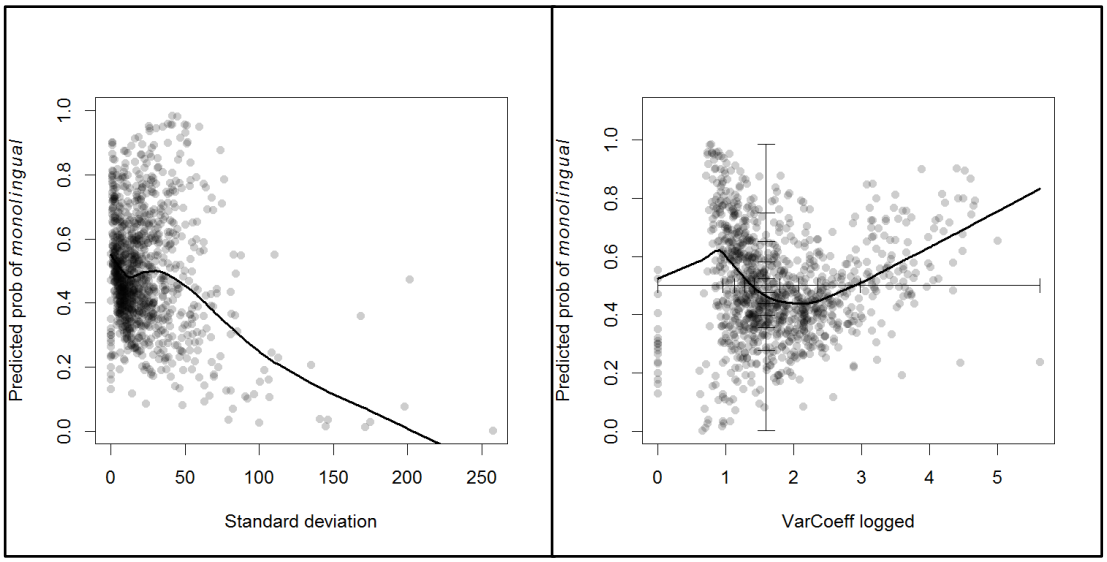

Figure 3.1:The main effects SD (left) and VARCOEFFLOG (right) Note: the tick-marked cross in the right panel indicates quantiles.

3.3.2.2. Interactions

Let us now turn to variables participating in interactions relevant to the present chapter's discussion, namely, the effects related to lemma frequency. Interestingly, there are two interactions that involve the corpus-based frequency of the lemma and two ways of measuring the variability of the syllable, the first of which is represented in Figure 3.2. This shows that the correlation of LEMMAFREQ and SDLOG differs between speakers. More specifically, with high-frequency lemmas, the variability values of mono- and bilingual speakers do not differ, which means SDLOG cannot distinguish the speaker types. However, with words whose lemma frequency is below 9, monolingual speakers have lower SDLOG values.

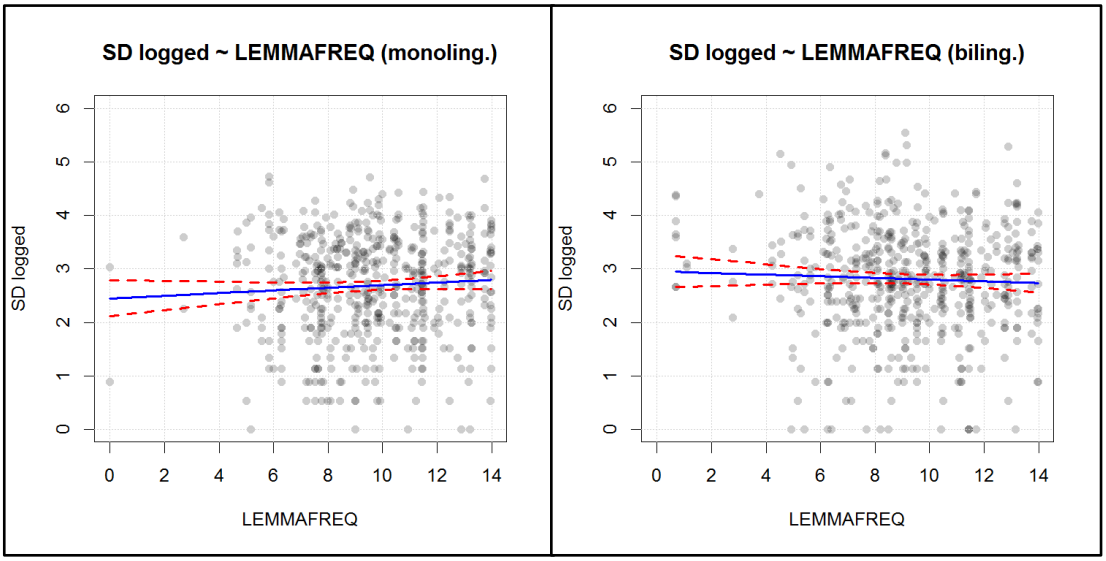

Figure 3.2: The interaction LEMMAFREQ : SDLOG

Figure 3.3 represents the interaction LEMMAFREQ : PVI. With medium and high-frequency lemmas, the variability values of mono- and bilingual speakers do not

differ, but otherwise the overall trends differ. For monolingual speakers, variability as measured by PVIs is positively correlated with LEMMAFREQ: more frequent words have higher PVIs than less frequent words, but it is the other way round for bilingual speakers. Also, the data show that PVIs can only distinguish mono- and bilingual speakers for words from the extremes of the frequency spectrum: lemmas with LEMMAFREQ<4 and with LEMMAFREQ>9.

3.4. Discussion: Multifactorial Analysis

3.4.1. Main Effects: SD and VARCOEFFLOG

As mentioned above, both significant main effects, SD and VARCOEFFLOG, are measures of duration variability which seem to predict opposite overall trends in speaker-

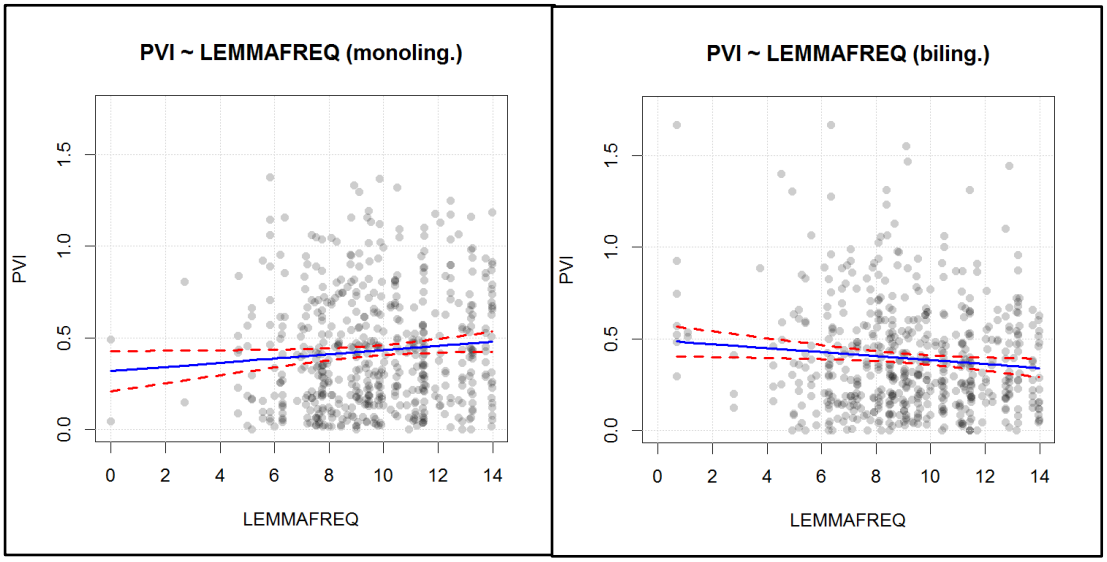

Figure 3.3: The interaction LEMMAFREQ : PVI

type: SD is positively correlated with bilingualism whereas the overall trend of VARCOEFFLOG is negatively correlated with it. That is, SD reflects the same trend observable for both the *Mean PVI* and *Raw PVI* calculations, namely that Monolingual Mexican speakers display more vowel duration variability than Bilingual Chicano speakers. Both SD and VARCOEFFLOG are calculated with the standard deviation of the vowel duration within an IU but only the latter controls for the mean syllable duration. This section will first discuss the main effect of SD and then VARCOEFFLOG.

It is SD that behaves more as would be expected by traditional rhythm class distinctions (but does not the reflect the hypothesis of the current chapter); due to the influence of English, the bilingual speakers' speech should be more variable in vowel duration than the monolingual speakers' speech, which is exactly what SD reflects. This is compatible with Low and Grabe (1995, 2000), Fought (2003), and Carter (2005, 2007). The former studied L1 vs. L2 speakers, finding that Singapore English tended to be more syllable-timed than British English. The speakers in the two latter studies were more similar to those of the current study, in that participants were bilingual, and Chicano speakers of Spanish and English, although both studies examined English rather than Spanish. In those studies, the English of Spanish-English bilinguals was more uniform and syllable-timed (i.e. more 'Spanish like') than that of European- and African-Americans (in Carter 2005, 2007), once again suggesting the results reflected by SD, that is, that bilingual speakers would have more variability in vowel duration, reflecting a more 'English like' Spanish. It is important to note that all of the aforementioned studies used the PVI as a metric of duration variability whereas, in the current study, the PVI was not a significant predictor of speaker type (although it did participate in one significant

interaction); instead it was SD that reflected the expected influence of bilingualism. Keep in mind that while SD is intended to measure the same acoustic property as the PVI, vowel duration variability, it is calculated in an alternate manner. In addition to the differing IMs utilized between the aforementioned studies and the statistically significant effect of SD, the related VARCOEFFLOG reveals a more complex trend.

As mentioned above, at first glance the trend of VARCOEFFLOG appears to be the opposite of the expected trend and that reflected by SD: Figure 3.1 suggests an overall positive correlation, according to which monolingual speakers display more variability in vowel duration than bilingual speakers. In other words, it suggests that the Spanish of monolingual speakers is closer in rhythm to English than that of bilingual Spanish-English speakers; this, of course, is in agreement with the trend identified by the PVI in the first two statistical treatments described (*see* **Chapter 2**). However, the overall picture is more complex than a brief glance at the smoother might suggest (additionally it is more complex than the simplistic trend suggested in the earlier analyses of the PVI). In examining the present case of VARCOEFFLOG, it becomes obvious that, while there is an overall positive correlation, this is a case where the prediction is most strongly 'bilingual' in the small range of exactly intermediate variability. Meanwhile, the extreme ranges of variability largely lead to the prediction of 'monolingual'. In fact, as the course of the smoother line indicates when related to the quantiles, bilingual speakers tend to group around the mean of VARCOEFFLOG. This would indicate that monolingual speakers are able to employ a full range of vowel duration variability, ranging from zero variability to the most variable syllable pairs, whereas bilingual speakers tend to display an intermediate level of variability according to VARCOEFFLOG, displaying syllable

pairs that are neither very similar nor very different.

The fact that native Spanish speakers show a wider range of vowel duration variability than their bilingual counterparts may be related to the monolingual speakers' greater command of the Spanish language. Their aptitude in the use of the language as well as the ability to employ language across a variety of registers may allow them to employ different levels of variability in rhythms in different contexts, leading to the aforementioned effects of VARCOEFFLOG. In comparison, the bilingual Spanish speakers indicated that they primarily used Spanish in family situations, so their range of abilities, and perhaps range of duration variability, are likely to be far more constricted.

3.4.2. The interaction LEMMAFREQ : SDLOG

The two interactions involving word frequency both prove to be highly interesting as well as important in their implications for further research of speech rhythms. The first, LEMMAFREQ : SDLOG, indicates that monolingual speakers exhibit less variability in vowel duration (measured in SDLOG) for less frequent words. In other words, with common words, bilingual speakers behave like monolingual ones, but with uncommon words, bilingual speakers are less homogeneous. Once again, this may be explained by linguistic aptitude: on average, bilinguals will have less exposure and practice – in terms of both comprehension and production – and, thus, speak more slowly, with careful or measured pronunciation. At the same time, it seems that their lesser proficiency also manifests itself in more heterogeneous production especially for those words to which they are even less exposed to: words of low frequency. An example of this can be seen in Figure 3.4 below. In pronouncing the word '*matemáticas*', the bilingual speaker

pronounces the word more slowly (and perhaps more carefully); the bilingual speaker takes about .74 seconds to pronounce the word while the monolingual speaker takes about .69 seconds (neither of these words were phrase final, and both were the first mention of the word, so, in theory, phrase position and information structure should not affect the duration of these words, although this is simply one *ad hoc* example; it should also be noted that the bilingual speaker in the upper panel is female while the monolingual speaker in the lower panel is male).

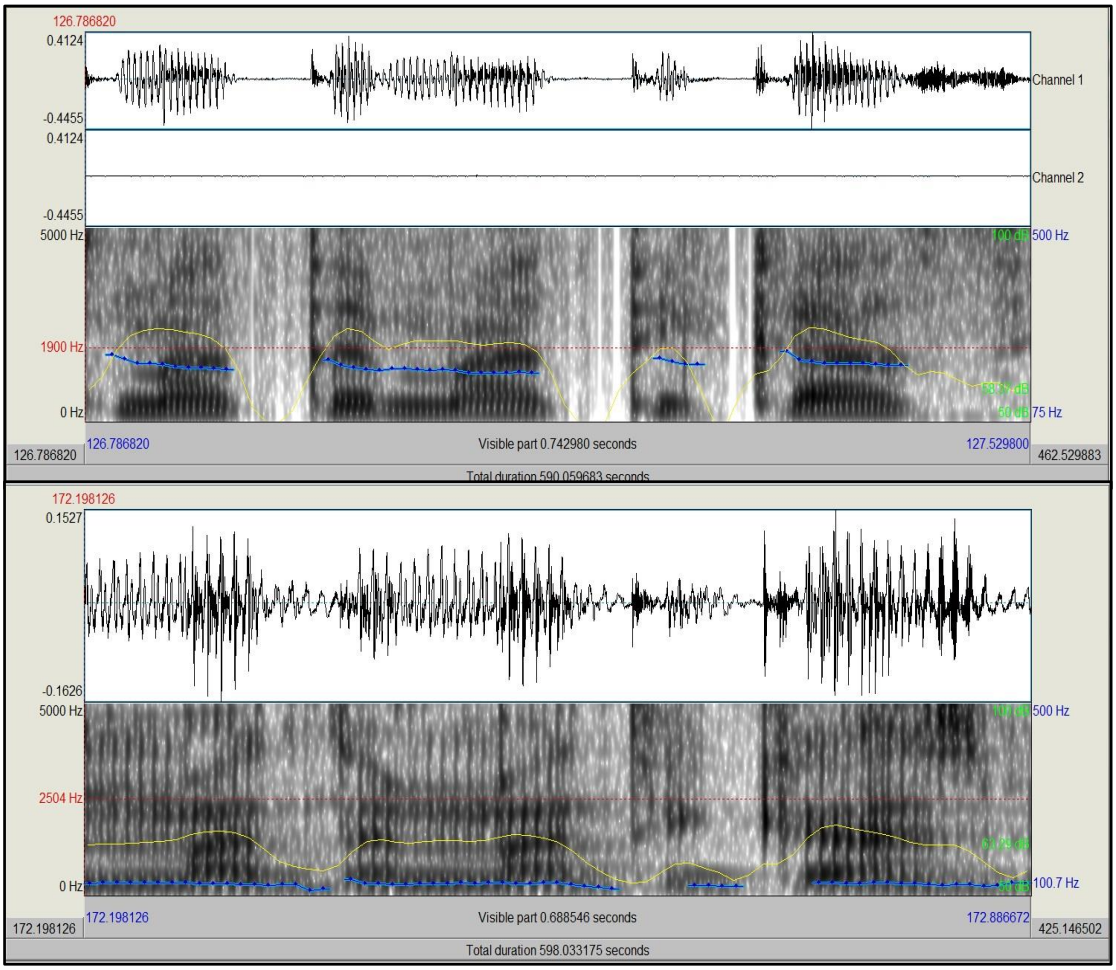

Figure 3.4: A waveform and spectrogram comparison of two pronunciations of a low frequency word, *matemáticas* (lemma frequency in Corpus del Espanol 20th Century Files (Davies, 2002-) = 2) in the current data. The bilingual speaker's speech signal is in the upper panel and the monolingual speaker's speech signal is in the lower panel.

3.4.3. The interaction LEMMAFREQ : PVI

The final interaction presently discussed in this chapter involves lemma frequency again, but this time with a different duration variability measure, the PVI. However, SDLOG and PVI themselves are positively (and exponentially) related (PVI≈0.02; 2.609 SDLOG; R2=0.86), which is why it is not surprising to see that this interaction is similar to LEMMAFREQ : SDLOG. Again, with less frequent words, monolingual speakers' duration variability is lower than that of native speakers. However, the present interaction shows that the PVI's effect is frequency-dependent just like that of SDLOG, but for a different range of lemma frequencies: SDLOG cannot distinguish speaker types with high frequency lemmas, but PVI can; SDLOG can distinguish speaker types with medium-frequency lemmas, whereas the PVI cannot. As an example of this, see Figure 3.5, which compares the pronunciation of the high frequency word Spanish *porque* by the same speakers as Figure 3.4, a bilingual female (upper panel) and a monolingual male (lower panel). Note that in this case, the bilingual speaker's speech is actually quicker than that of the monolingual speaker.

Since two measures of duration variability interact with LEMMAFREQ, this raises the question of how they compare to each other. On the one hand, it seems as if the PVI can distinguish the two speaker types over as wide a range of lemma frequencies as SDLOG, even if it is two non-consecutive ranges, high- and low-frequencies, but not intermediate ones. However, it must be borne in mind that frequency ranges of words are not all equally populated: frequencies are Zipfian-distributed, which means that there are very many words of low frequency, intermediately many words of medium frequency, but only very few words of high frequencies. Thus, the fact that the PVI can distinguish

speaker types for high-frequency lemmas better than SDLOG does not make it a more appealing measure because that will only include very few lemma types – by contrast, the fact that SDLOG can distinguish speaker types for all lemma types with a frequency of less than 9 makes it a more widely applicable measure.

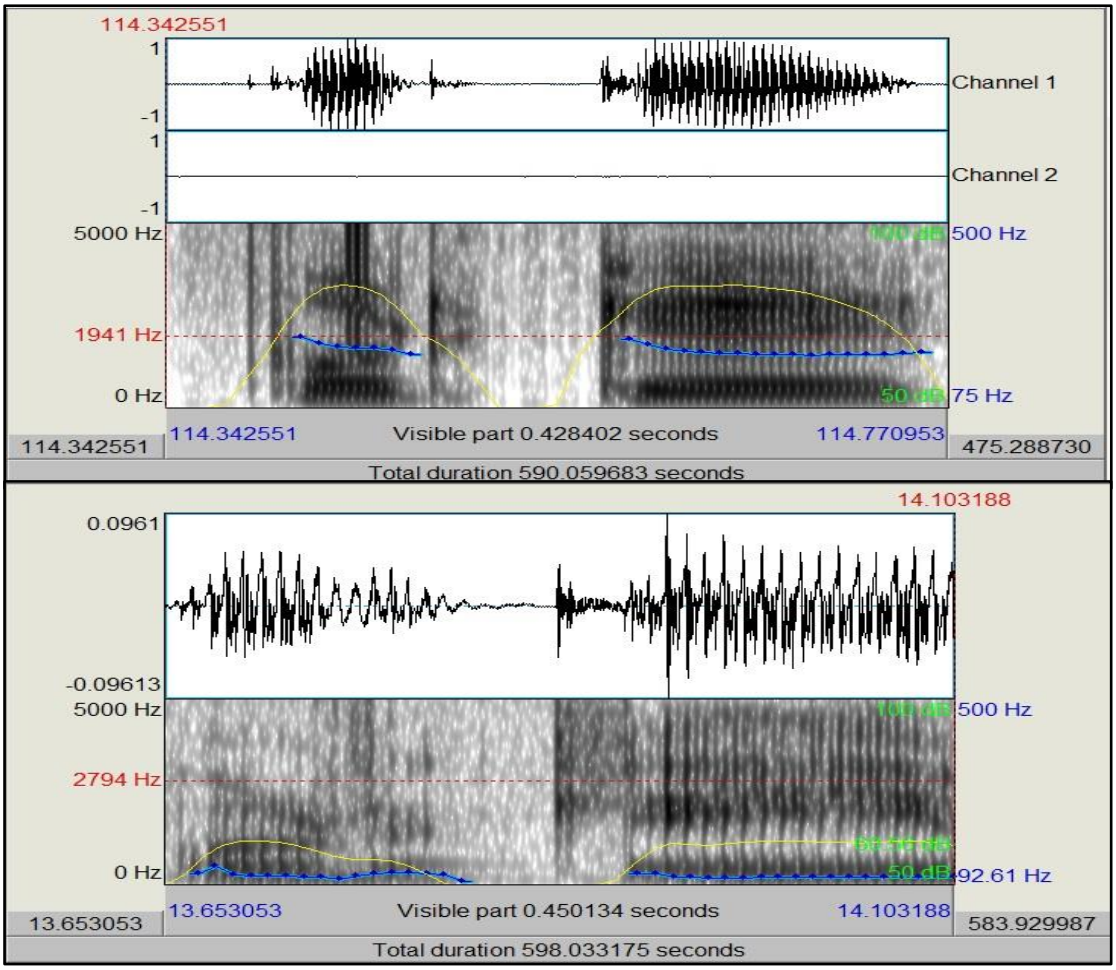

Figure 3.5: A waveform and spectrogram comparison of two pronunciations of a high frequency word, *porque* (lemma frequency in Corpus del Espanol 20th Century Files (Davies, 2002-) = 35,958) in the current data. The bilingual speaker's speech signal is in the upper panel and the monolingual speaker's speech signal is in the lower panel.

3.5. Implications

The findings discussed above lead to a general conclusion, which in turn entails two more specific implications. This general conclusion is that the multifactorial method employed in the current chapter provides a much more fine-grained perspective than the more simplistic methodologies of Chapter 2. The non-linear trend observed in the main effect VARCOEFFLOG for instance, would not be clear with a simple linear regression and the simplistic use of the PVI is virtually useless as a metric for the comparison of speech rhythms. Furthermore, interactions between predictors display important trends that would not be clear without the methodology employed. This is to say that in investigating a facet of linguistics as complex as speech rhythms, it is crucial to use the methodology best suited to the data, taking special care to utilize all the modern computational methodologies available (this fact, of course, is not exclusive to speech rhythms, but applies to all fields of linguistics). The first more specific implication is that the data shed further doubt on the utility of the PVI, especially given the results of Chapter 2. The PVI is simplistic in summarizing the complexity of vowel duration variability, and, by extension, speech rhythms. In the case of the *Mean PVI* and *Raw PVI* analyses, the PVI's high variability for individual speakers prevents a final model with low prediction accuracy (particularly in the case of Raw PVI), meaning that it is not ultimately useful in the quantification of vowel duration variability. In the case of the multifactorial analysis, the PVI does not feature as a main effect in the final regression model and only features in one interaction (with LEMMAFREQS); its classificatory power is therefore more limited than that of other predictors. Also, even within said interaction, the PVI's classificatory power is restricted to a smaller subset of the data than the competing measure of SDLOG:

this is to say that the range of words for which the PVI will be useful is smaller than that of SDLOG. In addition to these empirical findings, it is worth restating the design weaknesses of the PVI. On the one hand, the PVI as often used is a mean of means of means. However, it is well-known that means are really only appropriate measures of central tendencies for normally-distributed data, and in the data, the PVIs of 18 of the 20 speakers are significantly different from normality (and one of the two remaining speakers' PVIs are very close to that, too, with $p_{\text{Shapiro-Wilk test}}=0.051$). Related to this, the 'nested averaging' simply ignores a lot of variability that a more comprehensive approach would want to account for. For example, the 'nested averaging' also does not allow one to study PVIs on a syllable-by-syllable basis (since only an average will be considered in the traditional approach), and rules out the incorporation of, for instance, frequency effects for lemmas (as in the current chapter), words, syllables as well as other lexically-specific predictors.

Second, it is clear that such measures interact with corpus-derived lemma frequencies. It is interesting to note in this connection, however, that it is *lemma*, not *token* frequency that is more relevant to the speakers in the present data, which is surprising since usually word/token frequencies are more decisive for process of articulation. Regardless of which type of frequency will turn out to be more relevant to duration variability, future studies should not only try to approach duration variability in quantitatively more advanced ways (i.e., multifactorially) but also take frequency effects based on corpus data into consideration.

With regard to the utility of different measures in general, such data as could be useful to explore which of the measures result in the largest discriminatory power. With

regards to the study of speech rhythms, several statistical steps are self-evident, given the results discussed in this chapter. Findings like these indicate why measures such as the PVI may be too simplistic – the multiple averaging decontextualizes all variability – and why even the present approach can only be a starting point to explore duration variability in the rich and authentic contexts in which it occurs. For this reason, in order to evaluate speech rhythms, it is essential to 1) assess the data in a multifactorial manner, thereby assessing all relevant metrics and avoiding pitfalls, such as the overgeneralization of the PVI mentioned above, and 2) include corpus-based frequency effects, which have been shown to affect various areas of pronunciation, including duration variability. Thus, the researcher avoids picking and choosing those metrics that conveniently reflect apparent rhythmic differences, and are easily assessed and summarized, and, instead, allows the admittedly complex data set to be reflected in a statistically sophisticated and methodologically sound manner.

Finally, it is not enough to only include production data in the assessment of speech rhythms. It is clear that perception plays a major role in distinguishing rhythms (e.g. Nazzi, Bertoncini, and Mehler 1998), therefore the remaining chapters of my dissertation will concentrate on that aspect of human cognitive abilities. Perception data will be the starting point to define rhythmic classes of utterances, empirically evaluating speech rhythm perception, then this rhythmic classification will be used as the dependent variable in a multifactorial analysis of speech rhythm production.

This methodology avoids the error of assuming that different languages inherently belong to different rhythm classes and instead relies upon experimental data to determine rhythmic differences from a perceptual standpoint. It then employs current computational

methodology in assessing speech rhythm perception, using the methods described in the current chapter as a starting point.

The remainder of the dissertation follows this structure: **Chapter 4** assesses perception experiments of English, Portuguese, and Spanish speech rhythms. **Chapter 5** analyzes production data collected in an exhaustive experiment spanning native speakers from different languages on opposite ends of the syllable-timing vs. stress-timing spectrum. Finally **Chapter 6** will be devoted to the conclusions that can be drawn from these studies, their implications for the field of linguistics and future developments in speech rhythm research.

Chapter 4

Perception of English, Portuguese, and Spanish Speech Rhythms

Overview

This chapter describes several experiments performed in order to evaluate the perceptual differences in the speech rhythms of English, Spanish, and Portuguese. While perception experiments have been performed in the past (e.g. Ramus and Melher 1999), the current methods employed seek to both a) determine the relative position of these utterances of the three languages on the speech rhythm continuum and b) use these relative rankings as the dependent variable for a multifactorial analysis of the production of these same three languages (*see* **Chapter 5**). Thus, by using perception as the basis for an exploration of production, this study avoids a common pitfall of language rhythm studies, namely the assumption that all utterances of a language belong to the same rhythm class. After an introduction, two pilot studies and a third larger-scaled perception experiment are presented. In the conclusion, the results of these experiments are discussed in the wider context of this dissertation; in particular, their relation to the statistical evaluation in **Chapter 5** is presented.

4.1. Introduction

Given the results of the experiments described in **Chapter 2** and **Chapter 3**, the current chapter seeks to quantitatively evaluate the perception of speech rhythms of English, Portuguese, and Spanish. More specifically, the results of these chapters suggest that one cannot rely upon a single metric in order to attempt to differentiate between rhythm

classes in data; this is an especially important point given the fact that there is evidence of within-language (and within-speaker) variation (e.g. Loukina et al. 2009). Metrics of speech rhythm appear to participate in interactions and non-linear behavior, suggesting the need for a sophisticated statistical analysis of speech rhythm data. However, an additional consideration is necessary before addressing speech rhythm metrics. The parallel development of instrumental measurements as correlates of language-rhythms and perception-based studies, as seen in **Chapter 1**, suggests the next logical step, namely a combination of perception and production methodologies. This has been achieved in part by Ramus, Dupoux, Zangl, and Mehler's (2000) use of previous IM measurements from Ramus, Nespor and Mehler (1999). However, three characteristics of a methodologically sound study of language-rhythms are necessary. Firstly, one must use an advanced statistical evaluation of the data (e.g. the multifactorial statistical approach to acoustic correlates employed in **Chapter 3)**. Secondly, it is not sufficient to only include vowel duration cues in evaluated language rhythms. Syllabic durations (Deterding 2001) and correlates of lexical stress (i.e. duration, but also F0 and intensity) must also be included in said analysis; duration, intensity, and pitch have been shown to increase for stressed syllables (e.g. Marshall, Charles W. and Patrick W. Nye, 1983). Thirdly, speech low-pass filtering (Arvaniti 2012) must be applied to a perception study, while the statistical analysis of the production is performed upon the same utterances used in the perception study. That is, without making assumptions about the rhythmic classes, this methodology allows the exploration of which acoustic cues, if any, cause perceptual differences, regardless of language.

The following section will first describe the conceptual design behind the language rhythms perception experiment. Following are three experimental processes. The first two are pilot studies intended to evaluate and improve methodology employed in this chapter's perception experiment. The third is a rhythm perception test with 20 university students. Each experiment will include information about experimental design, data, statistical processing, and results. Finally, the conclusions of this chapter will be discussed, as well as how these conclusions determine the methodology employed in **Chapter 5.**

4.2. Perception Experiment: Conceptual Design

As previously mentioned, speech rhythms were originally discussed as a perceptual difference (e.g. Pike 1945); to use of the words of Barry, Andreeva, and Koreman (2009), "rhythm typology has its roots in auditory observation." At this point, it was assumed that languages of different rhythm classes all differ from one another rhythmically. However, this assumption has not been empirically proven; for example, no one has conclusively demonstrated that all Spanish utterances differ from all English utterances (although it has been shown that some Spanish utterances differ rhythmically from some English utterances). In fact, while some languages do appear to differ from one another in terms of (broadly-defined) speech rhythms, there is also a substantial amount of within-language rhythmic variation (Loukina, Kochanski, Shih, Keane, and Watson 2009). The experiments described in the current chapter attempt to ascertain whether utterances of English, Portuguese, and Spanish differ in an intra-language manner, an inter-language manner, or both. That is, this study compares English to Spanish, English to Portuguese,

but also English to English (etc.) in a perception experiment. The purpose of this is twofold. It is, of course, one of the major goals of this dissertation to quantitatively evaluate the relative positions of these three languages on the speech rhythm continuum. A second goal of this chapter is to use the analysis of these utterances as the dependent variable in a multifactorial study of the production of these utterances, reported in **Chapter 5**. Thus, rather than assume that all utterances of different languages represent different rhythm classes, the current study will first evaluate the perceptual differences of these languages and create a hierarchy of the various utterances used. In the following chapter, a multifactorial analysis of these utterances will investigate which (if any) production metrics prompt these perceived rhythmic differences.

Mexican Spanish, Peninsular Portuguese, and American English comprise the languages that provide utterances to be used as production and perception data for the current study. The opposite rhythmic classification of Spanish and English provide optimal samples of the opposing extremes of the speech-rhythm continuum. Meanwhile, Portuguese has a somewhat intermediate classification; Frota and Vigário, (2001) assessed the rhythmic typologies of both varieties of Portuguese (Brazilian and Peninsular) using the rhythm metrics introduced by Ramus, Nespor, and Mehler (1999) and determined that they display mixed rhythms. Peninsular Portuguese is characterized by a mix of stress and syllable-timed characteristics, while Brazilian Portuguese displays syllable-timed and mora-timed characteristics, suggesting that the speech-rhythm continuum is not solely comprised of more or less stress or syllable-timed languages. Furthermore, Frota, Vigário, and Martin (2002), demonstrated that, under certain conditions, European Portuguese

adults could distinguish filtered Peninsular and Brazilian Portuguese utterances from the reportedly more stress-timed Dutch.

As Peninsular Portuguese has been assessed as having an intermediate classification, displaying some stress-timed characteristics and some syllable-timed characteristics, this variety appears to have a central or mixed rhythmic typology. This provides an optimal language as it should fall between the two extreme poles of the speech rhythm continuum, syllable-timed Spanish and stress-timed English. Thus, the expected resulting classification of the test languages, according to traditional rhythmic typologies is illustrated in Table 4.1.

Poles of Rhythm Continuum	More Syllable Timed		More Stressed Timed
Proposed phonetic characteristics	less variable segment durations		more variable segment durations
Languages	Spanish	Portuguese	English

Table 4.1: Expected Position of test language on Speech Rhythm Continuum

As illustrated in Table 4.1, the traditional rhythmic distinctions suggest that the test languages would manifest themselves in the rhythmic hierarchy, ranging from the most stress-timed, English, to the most syllable-timed, Spanish, with Peninsular Portuguese falling somewhere between the two in perception data.

The perception studies described in this chapter rely upon the low-pass filtering methodology (e.g. Melher et al. 1988) rather than the speech resynthesis methodology (e.g. Ramus and Mehler 1999). Although recent speech rhythm studies have employed

both methodologies (e.g. Arvaniti 2012 for low-pass filtering; White et al. 2012 for speech resynthesis), and both methodologies have been defended (see **Chapter 1** for discussion), the current study follows Arvaniti (2012) in using low-pass filtering because the process is more faithful to the original speech signal. A more authentic prompt is conceivably more reliable in reflecting speech rhythm perception. Upon low-pass filtering at 450 Hz, non-syllabic information has been removed from the utterances (Arvaniti 2012); participants in the current study heard three low-pass filtered utterances and were cued to state which two utterances out of the three were most similar. Thus, without relying upon traditional rhythm class distinctions, the true manner in which languages are perceived is evident. By extracting a sufficient number of similarity ratings for UTTERANCE pairs, it is possible to statistically determine which utterances are most similar by performing cluster analysis using the hclust function for R (R Development Core Team, 2013).

A word about the maternal languages of the participants in the perception study is necessary. Although the ability to distinguish between two different speech rhythms is presumably universal, especially considering the work showing infants abilities to distinguish speech rhythms (e.g. Mehler et al. 1988), the native language of the participants could affect the data. Thus, although the current experiment does not restrict participants in the perception test according to native language, it does explore variation amongst the participants in order to prevent the skewing of data by individual participants/ and or 'nationalities' (as indicative of native language spoken, see Figure 4.2 and Figure 4.3).

4.3. Perception Experiment: Pilot Studies 1 and 2

The task in this experiment relies on participants' ratings of the similarity of various utterances. However, unlike previous experiments, which rely upon scale ratings (eg. Arvaniti 2012), this experiment relied upon direct comparison between various utterances. That is, the participants were presented with three utterances and then asked which of two among the three were most similar. As previously mentioned, the current study uses low pass filtering (Mehler et al. 1988) rather than speech resynthesis (Ramus and Mehler 1999).

4.3.1. Experimental design

Two English, two Portuguese, and two Spanish utterances were selected from a corpus of semi-directed interviews representing spontaneous speech; as previously mentioned, "[i]t is well known that there are differences between read and unscripted speech" (Deterding 2001:220). Each set of two utterances of one language came from the same speaker. The speakers were all females enrolled in a four-year university located in California, Lisbon, and Mexico City respectively at the time of recording and each was a monolingual speaker of their language. Utterances were chosen by the author and verified by a second phonologist to be similar in length and syllable number, to contain minimal pitch excursions, and to display similar levels of mean pitch. The following steps were undertaken to prepare the utterances for the experimental task: 1) Scale times to start at 0 seconds and end at 10 seconds; 2) Scale peak amplitude to .99; 3) Scale intensity average intensity to 70 dB; 4) Low-pass filter utterances at 450 Hz. See Figure 4.1.

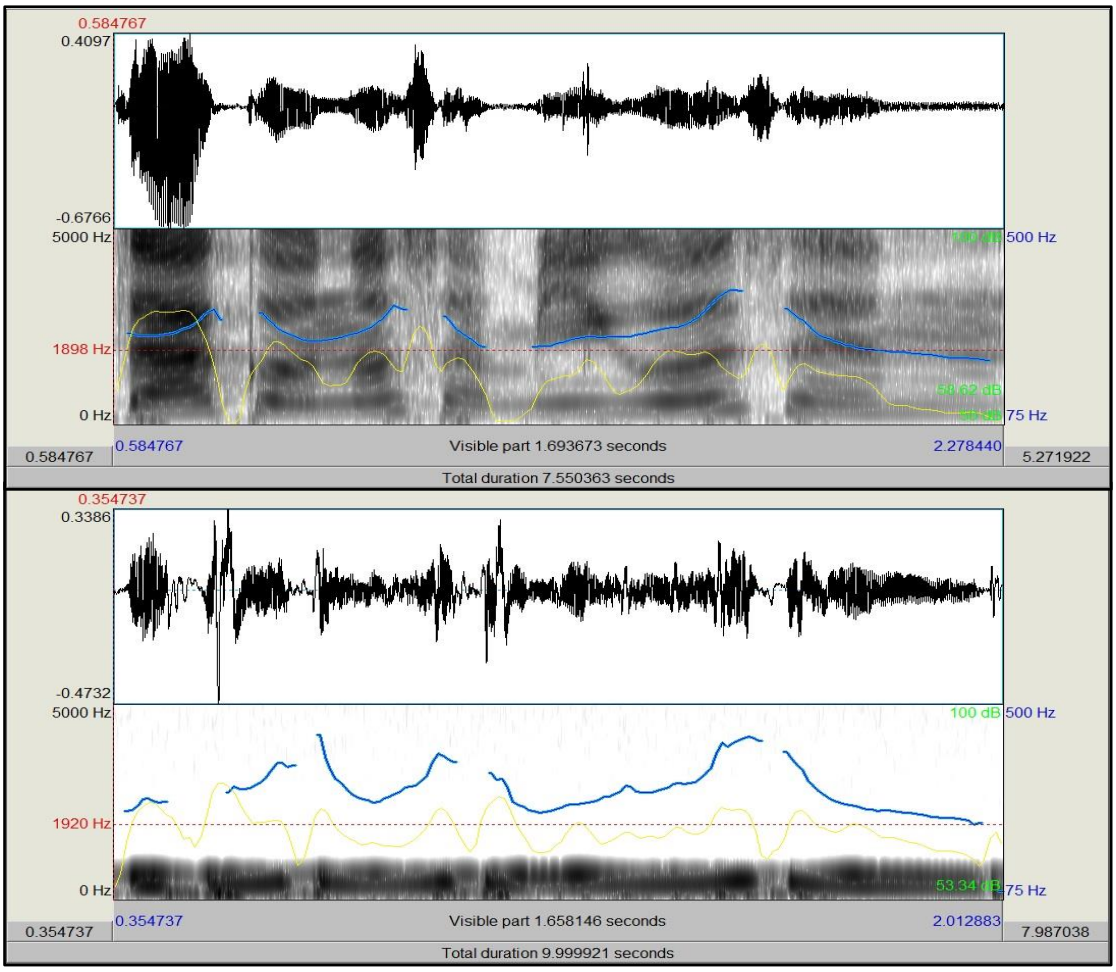

Figure 4.1: A comparison of the unedited Spanish utterance in the top panel and the low-pass filtered utterance in the lower panel, as used in the current perception experiments. This phrase is "*esta(b)a con (u)nos amigos en*."

After hearing each group of three utterances, participants were prompted to indicate which two utterances of the three were more similar. No further instruction or training block was used to prepare participants for the task. The training block was not necessary for two reasons. Firstly, differences in speech rhythms are theoretically perceptible universally, regardless of the native language of the listener; infants are able to distinguish rhythmic cues in language discrimination tasks (see Mehler et al. 1988 for low-pass filtered data and Ramus and Mehler 1999 for speech resynthesis data) and

speech timing seems to be biologically hard wired into the speaker (Wretling and Eriksson, 1998). Secondly, due to the utterance selection and low-pass filtering mentioned above, in theory only rhythmic cues were available to participants, although non-rhythmic cues (e.g. intensity, F0) were included as independent variables in the analysis of **Chapter 5** to allow for the possibility that these cues were salient to participants. Two different methods were piloted using these experimental cues. The following sections will describe these two pilot studies and the conclusions as to experimental design drawn from these pilot studies.

4.3.2. Perception Study: Pilot Study 1

For reasons of efficiency, the first series of experiments that comprise the data for *Pilot Study 1* were administered to participants in groups. The participants were the members of beginning Spanish and Portuguese classes. Three total classes were tested in this experiment: 11 students of an elementary Spanish class, 18 students of an elementary Spanish class, and 14 students of an elementary Portuguese class. Although it is possible that this language learning would somehow bias the rhythmic perception of participants, this fact was deemed inconsequential for three reasons. Firstly, as mentioned, rhythm is theoretically a universal difference that exists between languages of different classes. Secondly, these students were all in first-year language classes, so it is questionable that minimal language instruction would significantly alter their perceptions of speech rhythms, especially given that it appears that rhythm perception is acquired at a very young age. As mentioned in **Chapter 1**, Nazzi, Berteconi, and Mehler (1998), for instance, showed that French neonates could discriminate between a mora-timed language

and a stress-timed language. Thirdly, as these series of tests served as a pilot experiment, the main goal was to finalize methodology to be used; thus the availability of participants, rather than participant selection, was the most important facet of this pilot study.

The six low-pass filtered utterances were grouped into the twenty possible sets of three utterances without repeating the same UTTERANCE twice in any set. For each of the three classes, these sets were all randomized, both in the order of the twenty sets presented, as well as the order within which each set of three was presented. (See Table 4.2 for all the combinations of utterances used in *Perception Study: Pilot Study 1* and *Perception Study: Pilot Study 2.*) These randomized orders were presented in a slide show. The slide show informed students of which set (1-20) and which clip (1-3) within each set was playing. This was intended to keep students informed of what set was being tested during the study. The students responded to the question by hand on a response sheet distributed at the beginning of each experiment. The response sheet included a participant's consent to participate. In then asked for the participant's name, age, and native language. Finally, it had the following instructions: "You will hear a series of sets of three audio clips. After listening to all three clips, circle a, b, or c to indicate which two clips are most similar. You will only hear each set one time each." (see *Appendix X* for the response sheets used). The slide show and accompanying audio clips were played using the in-classroom media set up with consisted of a projector and two speakers. After the experiment performed, a brief discussion was conducted with the participants. Firstly, participants were asked for feedback on the task they had performed, such as length of task, ease, potentially confusing elements, etc.

This original pilot study revealed several methodological shortcomings. Firstly, from a conceptual standpoint, administering randomized orders of prompts to large groups of students at one time is questionable. It is difficult to ensure that each participant group is the same size, which makes controlling the potential variation between randomized orders difficult to say the least. Beyond this, controlling environmental factors becomes difficult. Auditory issues such as construction and grounds keeping tools being used near the classroom made it difficult for some students to hear the prompts. Furthermore, as the students sat at various distances from the speakers, some students heard the prompts at a louder volume as compared to others, and there was variation classroom to classroom in the volume at which the media equipment played the prompts. In fact, media equipment failure made it impossible to finish one of the classroom experiments. Finally, the students themselves voiced two major issues: firstly, it was difficult to follow along with the different clips being played, due to the difficulty of writing responses on the response sheet while simultaneously attempting to view the screen indicating which clip was being played; secondly, the experiment was too long. It took nearly 20 minutes to complete all the varying sets of clips, and participant fatigue played a major factor. Some students stopped answering questions towards the end of the survey, others circled only one letter answer to all the final questions, or wrote "I don't know." As mentioned above, only two of the three participant groups were able to complete the task, and even the complete data that was gathered still had some shortcomings as discussed above; for this reason, I will not discuss any results of these experiments. Instead, these pilot experiments served to optimize experimental design, leading to the second pilot experiment described in the following section.

Set	Clip 1	Clip 2	Clip 3
1	Portuguese 1	Portuguese 2	Spanish 1
2	Portuguese 1	Portuguese 2	Spanish 2
3	Portuguese 1	Spanish 1	Spanish 2
4	Portuguese 2	Spanish 1	Spanish 2
5	Portuguese 1	Portuguese 2	English 1
6	Portuguese 1	Spanish 1	English 1
7	Portuguese 1	Spanish 2	English 1
8	Portuguese 2	Spanish 1	English 1
9	Portuguese 2	Spanish 2	English 1
10	Spanish 1	Spanish 2	English 1
11	Portuguese 1	Portuguese 2	English 2
12	Portuguese 1	Spanish 1	English 2
13	Portuguese 1	Spanish 2	English 2
14	Portuguese 1	English 1	English 2
15	Portuguese 2	Spanish 1	English 2
16	Portuguese 2	Spanish 2	English 2
17	Portuguese 2	English 1	English 2
18	Spanish 1	Spanish 2	English 2
19	Spanish 1	English 1	English 2
20	Spanish 2	English 1	English 2

Table 4.2. All combinations of utterances combined to comprise the 20 sets used in *Perception Experiment: Pilot Study 1* and *Perception Experiment: Pilot Study 2.*

4.3.3. Perception Study: Pilot Study 2

Following the first pilot study, two major issues needed to be addressed. Firstly, the fact that the number of students in each classroom differed made it more problematic to control for the potentially biasing order in which the prompts were presented to

participants. If there are differences according to the order in which the utterances are presented to the participants, the method used in *Perception Pilot Study 1* would make it more difficult to account for this statistically. Secondly, as mentioned, environmental differences classroom to classroom make this approach less than optimal. Thirdly, some students found it difficult to listen to the clips and respond by hand while keeping their place during the task. In order to address these issues, *Perception Pilot Study 2* was undertaken in order to design a computerized version of the same task. By using headphones and a computerized testing program, pseudorandomization of the prompts was possible and the potentially biasing environmental issues were eliminated.

The computerized test was designed using Open Sesame (Mathôt, Schreij, and Theeuwes, 2012), an open source experiment builder for the social sciences. The computerized test followed these steps:

1. The experiment began with a participant consent form.
2. After this, participants were prompted to write their name and maternal language. The next screen gave instructions: "You will hear sounds clips 1, 2, and 3. After listening, indicate which clips are more similar. Wait just a moment…"
3. As each clip (utterance) played, the screen displayed to the participants which clip they were hearing (1, 2, or 3).
4. After the third clip, the screen asked participants, "Which are more similar?" and they were given the choice to respond with a mouse click:
    - "a. 1 and 2"

- "b. 2 and 3"
- "c. 1 and 3"

5. After responding, the participants saw as a screen that said, "Next set."
6. After completing the final set, the screen read, "You're all finished. Thank you!"

The main purpose of this second pilot study was to finalize methodology and experimental design. Thus, while this process was ongoing, several graduate students from the department of Spanish and Portuguese were recruited to pilot the experiment. Because many of these students were familiar with the nature of the experiment, none of the data logged from their participation was analyzed. However, feedback from these participants was valuable in trouble shooting both the design of the experiment and the functionality of the computerized testing program, as well as the automatic data logging process. Open Sesame automatically outputs data from experiments to spreadsheet software (Mathôt, Schreij, and Theeuwes, 2012).

After optimizing the computerized testing program, it still remained to evaluate the experimental task itself. As in *Perception Pilot Study 1*, participants indicated that the experiment was too long. One also attested that he began to recognize utterances from previous sets. Thus, it was determined that the experiment should be significantly shorter in order to avoid participant fatigue. Following this second pilot study, the final methodology to be used in the perception experiment was chosen, as described in the following section.

4.4. Perception Experiment

The experiment performed was very similar to the process of the *Perception Pilot Study 2*, as described in the previous section. The major difference in this case, however, is the number of sets of 3 utterances presented to each participant. In order to make the task shorter, the current experiment used a total of 7 sets of utterances, rather than 20, as in the previous experiment. Both the previous and current experiments used the same 6 utterances (2 English, 2 Portuguese, and 2 Spanish utterances). While *Perception Experiment 1*, relied upon all possible combinations of three utterances, the current experiment relies upon all possible combinations of languages, but not utterances. Compare Table 4.2 (above) to Table 4.3 (below) for all combinations of the utterances.

Set	Clip 1	Clip 2	Clip 3
1	Portuguese 1	English 1	Spanish 1
2	Portuguese 1	Portuguese 2	Spanish 1
3	Portuguese 1	Portuguese 2	English 1
4	Spanish 1	Spanish 2	Portuguese 1
5	Spanish 1	Spanish 2	English 1
6	English 1	English 2	Spanish 1
7	English 1	English 2	Portuguese 1

Table 4.3. All combinations of utterances combined to comprise the 7 sets used in *Perception Experiment.*

By reducing the number of prompts, the experiment took less than 10 minutes, rather than 20, as in the previous pilot studies. Apart from this difference, the experiment conditions were identical to those in *Perception Experiment: Pilot Study 2*, including the computerized testing program and low-pass filtering of the utterances.

4.4.1. Participants

The participants in the current study were students of an upper division Hispanic linguistics class at the University of California, Santa Barbara. They were offered extra credit in return for their participation in the study. As upper division Spanish students, all spoke Spanish at a native, heritage, or advanced level. Of the twenty participants, 11 self-identified as Spanish speakers, 8 self identified as English speakers, and 1 self-identified as a speaker of Cebuano. There were 14 females and 6 male participants. Table 4.4 gives demographic information for the participants.

Native Language	Female	Male	Total
Cebuano	1	0	1
English	5	3	8
Spanish	8	3	11
Total	14	6	20

Table 4.4. Demographic information for participants in *Perception Experiment.*

4.4.2. Data Collection

Open Sesame (Mathôt, Schreij, and Theeuwes, 2012) was once again used to test participants, who participated individually using a computer and headphones. Unlike the pilot test, five different pseudorandomized orders of the sets and prompts were used; these pseudorandomized orders will be referred to *Treatments 1-5*. As there were 20 participants, each pseudorandomized order was taken by four different students. The participants read and electronically signed a computerized consent form, then were prompted to write their name and maternal language. In this case, they were also prompted to write what number test they were taking; this was a safeguard to make sure that the correct pseudorandomized test was being given. After the preliminary steps, the students responded to the same instructions: "You will hear sounds clips 1, 2, and 3. After listening, indicate which clips are more similar. Wait just a moment…" After hearing each set of three clips, they responded to, "Which are more similar?" and they were given the choice to respond with a mouse click to "a. 1 and 2", "b. 2 and 3", or "c. 1 and 3." Finally, they saw a screen which read: You're all finished. Thank you!" The students' responses were automatically logged onto spreadsheet software by Open Sesame (Mathôt, Schreij, and Theeuwes, 2012).

4.4.3. Data treatment

After collecting the data, a cluster analysis using the function hclust from the package stats (R Core Team and contributors worldwide) was undertaken. Three questions were addressed in this data analysis: 1) Do the different pseudo-randomized orders (or treatments) behave in an idiosyncratic manner? 2) Do the participants behave in an

idiosyncratic manner? In other words, perhaps the participants may all consistently rank of the similarity of the utterances, or it is possible that different individuals or groups of participants behave idiosyncratically 3) Finally, after considering the preceding two questions, do the utterances themselves group in any particular manner? That is, is there any manner in which the utterances can be considered similar or dissimilar?

Regarding the first question, a cluster analysis was performed in order to see if any groupings of the treatments were visible. This process clusters the variables into successively smaller groups so that the variables within each cluster are maximally similar and the variables between clusters are maximally different (Everitt, Landau, Leese, and Stahl 2011). In the context of the current study, the cluster analysis groups the treatments according to their ratings of similarity. The current study used the curvature-based approach *correlation* and the method *ward.D*, which groups those elements whose elements increase the error sum of squares least when joined (Gries 2009:317).

Figure 4.2 suggests that there are some similarities in the treatments. In fact, the behavior or Treatments 1 and 5 are quite similar, while Treatments 2, 3, and 4 form a cluster, with Treatments 3 and 4 being the most similar of the three. This would indicate that there is no one treatment that is extremely different from the other treatments, although there may be some differences according to the pseduo-randomized orders. In consideration of the fact that there may be some biasing factor in the treatments, in addressing the potential idiosyncrasies in the individual participants' responses, the treatment number was also included after the participants initial in the dendrogram. This allows a more in-depth view of the manners in which the treatments may affect the participants' responses.

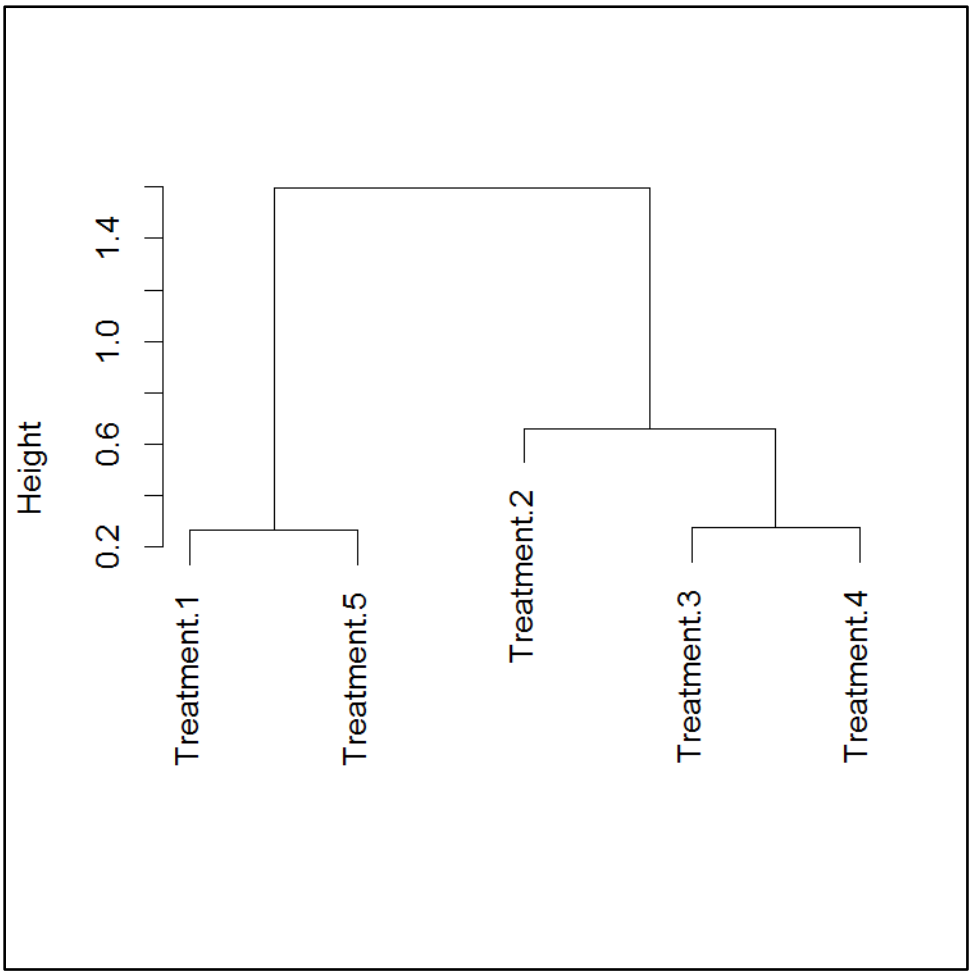

Figure 4.2. A dendrogram representing the similarity of the randomized orders presented to the participants. The relative distance is represented by the height along the y-axis

Regarding the second question, a similarity matrix was generated to determine how the participants rated the similarity of the various utterances. In this case, the languages were conflated due to relatively sparse data. That is, the utterances Spanish 1 and Spanish 2 were conflated as Spanish, Portuguese 1 and Portuguese 2 were conflated as Portuguese, and English 1 and English 2 were conflated as English. Using this similarity matrix, a dendogram was generated for all participants. After each participant's initials, the pseudo-randomized treatment order was included as well, in order to determine if the participants' grouping was influenced by the order in which they were

presented with the utterances. Figure 4.3 shows the dendrogram according to participants and the randomized order.

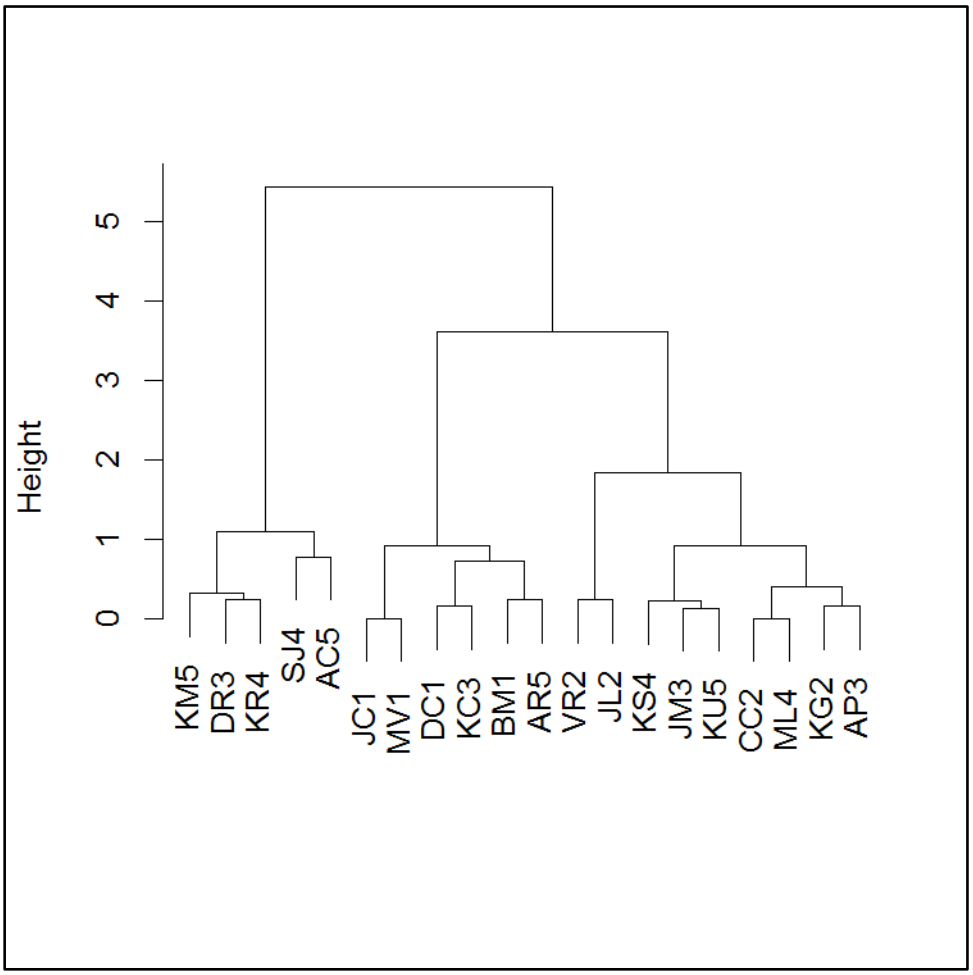

Figure 4.3. A dendrogram showing the participants (represented by name) and the pseudo-randomized order (1-5) in which they heard the utterances (represented by the number following the name)

Figure 4.3 shows several groups of participants. However, in the context of this experiment, it considers the three nodes indicated by the first two splits in the cluster tree. As previously mentioned, cluster analysis is an exploratory method. In considering the structure of the dendrogram, the three largest clusters provide both a reasonable size of participants to investigate, as well as a potential explanatory factor; in viewing the various

clusters, some of the pseudo-randomized orders occur in certain clusters. Specifically, the first pseudo-randomized order occurs exclusively in the second cluster from the left, and the second pseudo-randomized order in the third cluster, or node, from the left. Meanwhile, the third, fourth, and fifth orders seem to be distributed relatively evenly between the clusters.

Given the structure observed in Figure 4.3, a series of dendrograms demonstrating the manner in which the utterances clustered according to the participants' responses was generated, using the distance *manhattan* and method *ward.D*. The participants were grouped into three different groups based upon the three nodes in Figure 4.3. These dendrograms are represented in Figure 4.4.

Figure 4.4 shows three different dendrograms according to the participants' grouping from Figure 4.4. What is immediately apparent is that all three groups of participants consistently grouped the two Portuguese utterances as more similar, as compared to the other languages. For the remaining languages, one group was able to consistently classify the utterances according to language. Group 1, represented in the top left panel of Figure 4.4 not only grouped all utterances of the same language together, but also ranked the two Romance languages as more similar to one another as compared to English, a Germanic language; this would be expected based upon typology. The other two groups did display some cross-linguistic clustering, with utterances of Spanish and English being rated as more similar to one another, as opposed to the utterances of the same language.

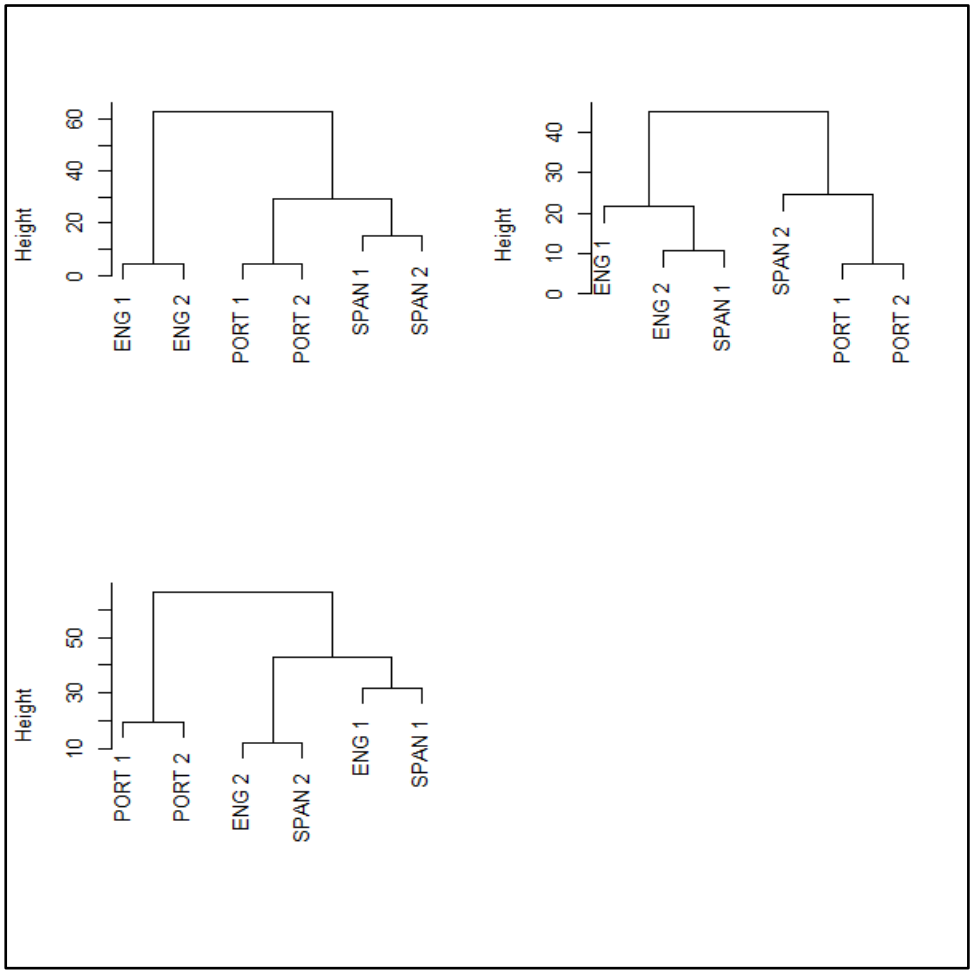

Figure 4.4. A dendrogram showing the grouping of the languages according to each participant group identified in Figure 4.3. Clockwise from the top left are Group 1, Group2, and Group 3

4.4.4. Results and Discussion

Given the results of the perception experiment described above, it can be concluded that the two Portuguese utterances can be considered as belonging to the same rhythmic class from a perceptual perspective. Meanwhile, the remaining utterances, English 1, English 2, Spanish 1, and Spanish 2, do not display consistent groupings, either across or within languages. This is due to the fact that some participants classify them as grouping more

similarly based on language distinctions, grouping Spanish with Spanish and English with English, while others classify them as grouping across languages, grouping certain Spanish with certain English utterances. Thus, it can be concluded that these utterances are all rhythmically different from one other, based upon the perception of participants in the current experiment.

This is noteworthy in that it is contrary to traditional rhythmic class distinctions. According to the typical concept of rhythm, Spanish and English should be maximally different, as they represent syllable and stress-timed languages, respectively (e.g. Carter 2005). Meanwhile, Portuguese is described as a more intermediate language, falling between stress-timed English and syllable-timed Spanish (e.g. Frota and Vigário 2001). Thus, from the perspective of traditionally described rhythmic distinctions, it would follow that Portuguese would be more likely to be perceived as similar to English and/or Spanish, while English and Spanish would be maximally different in terms of syllabic rhythm. However, as seen Figure 4.4, the case is the opposite. While Spanish and English are grouped together by some participant groups, Portuguese is never grouped with either Spanish or English. This would suggest that Portuguese is maximally different from English and Spanish, with participants rating Spanish and English as more similar. There are two potential explanations for this. The first is that Portuguese is in fact more rhythmically different from English and Spanish than the traditional rhythm class and rhythm continuum would suggest. This could be due to duration cues, such as vowel reduction, which occurs in Peninsular Portuguese (Macedo and Koike 1992). The second explanation is that the participants are not making the distinction according to traditionally defined rhythmic classes, but instead using other acoustic cues associated

with the utterances. Both of these questions are worthy of investigation, and prompt the statistical evaluation in **Chapter 5**, where both of these possibilities are investigated. **Chapter 5** undertakes a multifactorial analysis of the acoustic and duration correlates of the utterances used in the current perception experiment in order to evaluate what, if any, acoustic correlates potentially prompt these perceptual differences. If the former case is true and Portuguese is rhythmically distinct from English and Spanish, this will be theoretically reflected in one of the metrics intended to evaluate speech rhythms. Non-rhythmic cues are also included in the multifactorial analysis in order to account for the latter possibility, namely that participants are grouping these utterances according to some salient non-rhythmic cue. In order to ascertain what differences in the utterances caused the participants to maximally distinguish between all utterances except for the two Portuguese utterances, **Chapter 5** considers the acoustic properties of English 1, English 2, Spanish 1, Spanish 2, and combines Portuguese 1 and Portuguese 2 into a single variable, Portuguese.

Chapter 5

Production Data of English, Portuguese, and Spanish

Overview

This chapter describes the evaluation of the acoustic correlates of the utterances used in the aforementioned perception experiment of the speech rhythms of English, Portuguese, and Spanish. The main purpose of the approach is to identify acoustic variables that prompt perceived differences in rhythms. The following sections will describe the data and variables, statistical processing, results, and finally discuss the conclusions and implications of this data set. A series of *post hoc* analyses follow and then a final discussion concludes this chapter.

5.1. Data and Variables

5.1.1. Data

As mentioned, the variables in this chapter are derived from the utterances that were analyzed in **Chapter 4**. These 6 clips were culled from the specialized corpus of naturalistic speech of English, Spanish, and Portuguese. As mentioned in the previous chapter, 2 clips of each language (for a total of 6 clips from 3 speakers) were chosen from the corpus and verified by the author and another phonetician[7] to be similar in F0, lacking major pitch excursions, and lacking any major audible differences. They were then evaluated in a perceptual experiment according to their similarity in terms of syllabic rhythm. The two English and two Spanish clips were all shown to be maximally different,

[7] Thanks to Dr. Viola G. Miglio for her help in verifying the utterances to be used in the current chapter, as well as for her help in dividing them into smaller phonological units (see below).

while the two Portuguese clips were maximally similar. Thus the two Portuguese samples were combined into a single level of the variable UTTERANCE. This results in five levels of UTTERANCE: *English 1*, *English 2*, *Portuguese*, *Spanish 1*, and *Spanish 2*. The following sections will discuss how a variety of correlates of speech rhythms, as well as some additional prosodic variables, were derived from these utterances. In order to derive some variables, it was necessary to divide the utterances into phonological constituents. The next section will discuss how the utterances were divided into phonological constituents according to established guidelines. Next, the dependent variable and the independent variables analyzed in the current chapter are presented.

5.1.2. Variables: Phonological Constituents

It was necessary to divide the utterances into phonological constituents in order to calculate the standard deviations of certain phonological features (e.g. segment duration, intensity, and pitch). The standard deviation of segment durations are commonly used correlates in some speech rhythm studies (e.g. Ramus, Nespor, and Mehler 1999). However, it is not possible to include one single standard deviation for each utterance, as in Ramus, Nespor, and Mehler (1999), who use a mean standard deviation (of several utterances) for each speaker. In the current data set, this would lead to a one-to-one correlation between each utterance and the single standard deviation that represents it. The result of this one-to-one correlation is a model with one main effect (standard deviation) with perfect predictive power; this model is ultimately entirely uninformative as to the role of segment duration variability in the perception of speech rhythms. Thus it is necessary to include units of the utterance that are larger than the syllable yet smaller

than the entire utterance; these units are determined according to prosodic constituents. It is necessary to define the boundaries of prosodic constituents in order to investigate these effects and consider their role in rhythm perception.

Various phonological constituents comprised of prosodic units have been proposed. In a structural theory of stress and metrical prominence such as Metrical Phonology (Liberman 1975), for instance, prosodic prominence is no longer bound to specific segments, but rather to suprasegmental components. Prosodic or metrical components, in turn, obey the so-called Strict Layer Hypothesis (SLH, Selkirk 1984), whereby all components on one level of metrical analysis comprise all components from the level immediately below, and only those. These prosodic components are hierarchical in nature. Thus, prosodic constituent structure is laid out according to a 'prosodic hierarchy' as follows (Selkirk 1984):

- Utt Utterance
- IP intonational phrase
- PhP phonological phrase
- PWd prosodic word
- Ft foot
- σ syllable

While these constituents were largely motivated theoretically rather than empirically, they do provide a basis for the constituents used in the current study. However, due to the length of the utterances (approximately ten seconds each), the six prosodic constituents

listed above prove to be too many. Accordingly, the utterances were divided into four levels:

- Utterance
- Intonational Phrase
- Phonological Phrase
- Syllable

The process for the actual division of these units was based upon the division prescribed by the ToBI (for *Tones and Break Indices*) system (Beckman and Ayers Alam 1997). The ToBI system, which is used to transcribe the intonational patterns and other prosodic aspects of a language, is based upon the autosegmental metrical (AM) framework (e.g. Pierrehumbert 1980). The AM framework distinguishes between two types of tonal events involving F0: *pitch accents* and *edge tones*. The former events, *pitch accents*, are associated with the nucleus of a syllable while the latter events, *edge tones*, are associated with the boundaries of prosodic constituents (Ladd 1996). The ToBI system prescribes the labeling of these discrete intonational events in two different manners following Pierrehumbert and Hirschberg (1990), as cited in Beckman and Ayers Alam (1997:8). The ToBI system has, in fact, four different tiers for labeling:

1. a tone tier
2. an orthographic tier
3. a break tier
4. a miscellaneous tier

As the tone tier and the break tier "represent the core prosodic analysis" (Beckman and Ayers Alam 1997:8), this study is concerned with these two tiers. The tone tier is the location of the transcription of the two tonal events defined by the AM framework, namely *pitch accents* and *event tones*. The break tier allows for the labeling of groupings of prosodic constituents. This labeling is based on "the subjective strength of its [the current word's] association with the next word, on a scale from 0 (for the strongest perceived conjoining) to 4 (for the most disjoint)." (Beckman and Ayers Alam 1997:9, square brackets are mine). These break indices can be roughly defined as follows (from Beckman and Ayers Alam 1997):

1. "cases of clear phonetic marks of clitic groups"
2. "most phrase-medial word boundaries"
3. "a strong disjuncture marked by a pause or virtual pause, but with no tonal marks; i.e. a well-formed tune continues across the juncture OR a disjuncture that is weaker than expected at what is tonally a clear intermediate or full intonation phrase boundary."
4. "intermediate (intonation) phrase"
5. "(full) intonation phrase"

By considering these tone break labels in conjunction with the two types of tonal events labeled on the tone tier, the utterances in the current study were divided in the aforementioned prosodic units. It is worth mentioning that, in this division, it is not possible to consider the prosodic events solely; one must also consider the content of the

phrase. As Nolan states: “we can regard grammatical structure as determining the point at which intonational phrase boundaries can occur, but whether they do or not depends on performance factors” (2008:444). Thus, I considered the structure and content of the phrase as a determination of where a prosodic constituent boundary could occur, but the presence or absence of this boundary was determined by prosodic consideration, principally F0 and intensity, but also segment duration. Additionally, tone events that would be marked on the tone tier of ToBI were also considered in determining the division of the prosodic constituents. The following paragraph will describe the exact process of prosodic constituent division occurring to the units considered: *utterance*, *intonational phrase*, *phonological phrase*, and *syllable*.

The *utterances* were defined as the recorded sentences in their entirety. As mentioned, these utterances were all approximately ten seconds long and were culled from a corpus of spontaneous speech of native monolingual speakers of each respective language. See Figure 5.1.

The *intonational phrase* is equivalent to a break index of 4 in the ToBI system, or a full intonational phrase. Crucially, this is represented by an edge tone, to use the AM framework terminology, which is labeled as % on the tone tier in the ToBI system. The current analysis follows Selkirk (1978) in identifying the intonational phrase as the domain of the intonational contour. Furthermore, the end of an intonational phrase is the point where a pause could be introduced in the sentence (Nespor and Vogel 1986:188). See Figure 5.1.

The *phonological phrase* is equivalent to a break index of 3 in the break tier of the ToBI system, or an intermediate (intonation) phrase. Final lengthening occurs at the end

of the phonological phrase (Nespor and Vogel 1986). These breaks were determined in consideration of the prosodic properties of each case, rather than relying solely upon the lexical word at hand. Specifically, F0 and intensity were considered in this labeling process. Each phonological phrase could contain one or more accentual phrase, an accentual phrase contain a maximum of one pitch accent (Beckman and Pierrehumbert 1986)[8]; however, the current study distinguished phonological phrases from accentual phrases in that phonological phrases contain boundary tones (e.g. Nespor and Vogel 1986) while accentual phrases do not (*see* Beckman and Pierrehumber 1986 *for English*).[9] See Figure 5.1.

The *syllable* was defined primarily according to the syllabification of each lexical item. However, in special cases where the syllabification was inconsistent with the traditional lexical syllabification, the phonetic performance of the speaker was considered.

In addition to the previously mentioned grouping of prosodic constituents, the presence of lexical stress was coded. STRESS (*yes* or *no*) was simply determined as the location of lexical stress in a word as determined by the standard pronunciation of American English, European Portuguese, and Mexican Spanish (see Wilson 1993 for English, Hutchinson and Loyd 1996 for Portuguese, and Canfield 1981 for Spanish). This was labeled regardless of the actual presence or absence of stress as a prosodic event and, in conjunction with frequency affects and syllable structure, could be used to determine

[8] The current dissertation differs from Beckman and and Pierrehumbert in that is does not distinguish between the accentual phrase and the intermediate phrase as the utterances from which these units were determined were only about 10 seconds in length, and, thus did not require such differentiation.

[9] Note that in English, at least, the relationship between the accentual phrase and the prosodic word is not clear (Beckman andand Pierrehumber 1986:269-270).

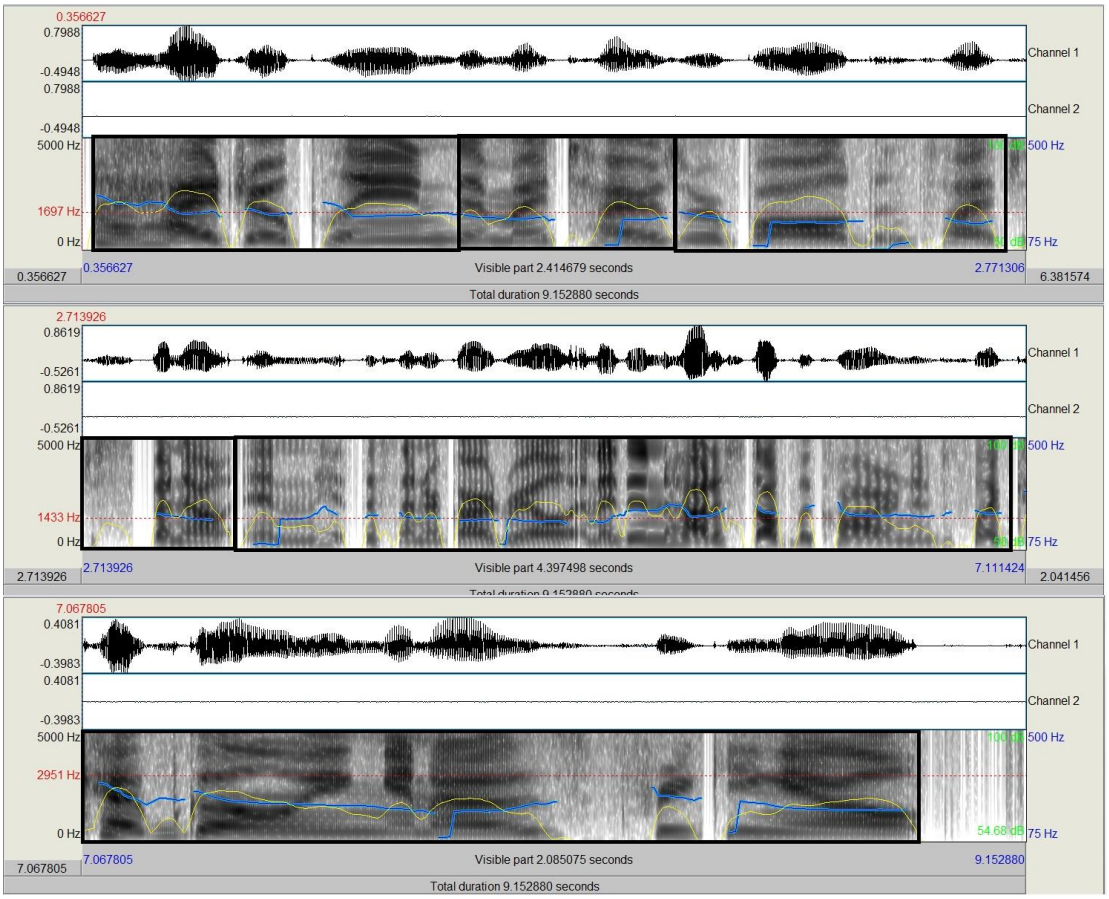

Figure 5.1: The utterance *English 1* divided into prosodic units as described in the current chapter. This utterance has been divided into three panels, with each panel representing an *intonational phrase*. These *intonational phrases* have been parceled into smaller *phonological phrases* where relevant. The utterance reads as follows, with curly brackets representing the *intonational phrase* and square brackets representing the *phonological phrase*: {[*I hydroplaned*] [*and my tires were bald*] [*and so I just*]} {[*spun out and*] [*hit the center guardrail and I didn't know how to stop the car and it just like kept going*]} {[*and I was freaking out*]}. For a complete representation of the data used in the current experiment, see Appendix 2.

probabilistic patterns that could affect rhythm due to the internal syllabic structure of a language. Thus, STRESS (*yes* or *no*) was coded according to prescribed lexical patterns of language, rather than the performance of the speaker. While it would have been possible to code this variable according to correlates of stress, such as pitch, duration, or intensity (Fry 1955, 1958), there was no compelling reason to expect that the performance of the participants would greatly deviate from prescribed lexical stress patterns given that they

were native speakers of their respective languages. Furthermore, the difficulty in distinguishing lexical stress from phrase-level stress (e.g. Ortega-Llebaria and Prieto 2007) makes the use of prescribed lexical stress patterns more practical. While this variable does not factor in the main Random Forest and multifactorial analyses in the current chapter, it was used in *post hoc* exploration of syllable duration.

Meanwhile, PITCHACCENT (YES or NO) was concerned with the presence of a pitch accent within a prosodic word, regardless of the supposed presence of a lexical accent. Following Fry (1955, 1958), this variable was defined as the presence of higher and/or changing F0, increased intensity, and/or increased syllable duration in order to mark prominence in a prosodic word or phonological phrase and was equivalent to a pitch event marked as * in the ToBI system. It has been traditionally held that in stress languages pitch accent can only occur on the syllable of a word bearing lexical stress (e.g. Goldsmith 1978). Thus, a syllable could be [+ stress, + pitch accent], [+ stress, - pitch accent], or [- stress, - pitch accent], but not [- stress, + pitch accent]. Thus, a pitch accent was considered as potentially capable of occurring in the lexically stressed syllable of a word.

5.1.3. Dependent Variable and Independent Variables

Given the results of the data exploration described in **Chapter 4**, the utterances were combined into the following five levels: English 1, English 2, Portuguese (comprised of Portuguese 1 and Portuguese 2), Spanish 1, and Spanish 2. Thus, UTTERANCE (*English 1, English 2, Portuguese, Spanish 1, Spanish 2*) serves as the dependent variables in a Random Forest analysis of the following variables.

These utterances were examined using PRAAT (Boersma and Weenink 2010) in order to record vowel duration, syllable duration, mean pitch, maximum pitch, minimum pitch for each vowel, and mean intensity for each vowel. Regarding the use of mean for pitch and intensity, one must consider the distribution of the data. Mean as a measure of central tendency assumes normally (or nearly normally) distributed data. In order to explore the distribution of pitch and intensity in the current data, the first 50 vowels of the data were examined in order to determine if the F0 and intensity were normally distributed. For each vowel, the intensity and F0 were measured every 10 milliseconds. Then the data points pertaining to each vowel were tested for normality of distribution using a Shapiro-Wilk test. For the 50 distributions of intensity, 27 were normally distributed and 23 were not. for the 50 distributions of F0, 27 were normally distributed and 23 were not. See Figures 5.2 and Figure 5.3. Although not all of the data tested were normally distributed, the current experiment considers the mean pitch and mean intensity measures for two reasons. Firstly, the majority of the data did not significantly deviate from normal distribution. Furthermore, it is quite common for linguists to consider mean pitch and mean intensity across a segment in prosody studies (e.g. Gervain and Werker 2013). Thus, the mean of F0 and intensity were adopted, especially given the fact that the use of mean affords a more direct comparison with correlates used in other studies. (Nonetheless, just like in the above critique of averaging across non-normal PVI-values, future work would be well advised to explore statistics other than the mean for subsequent statistical analysis.)

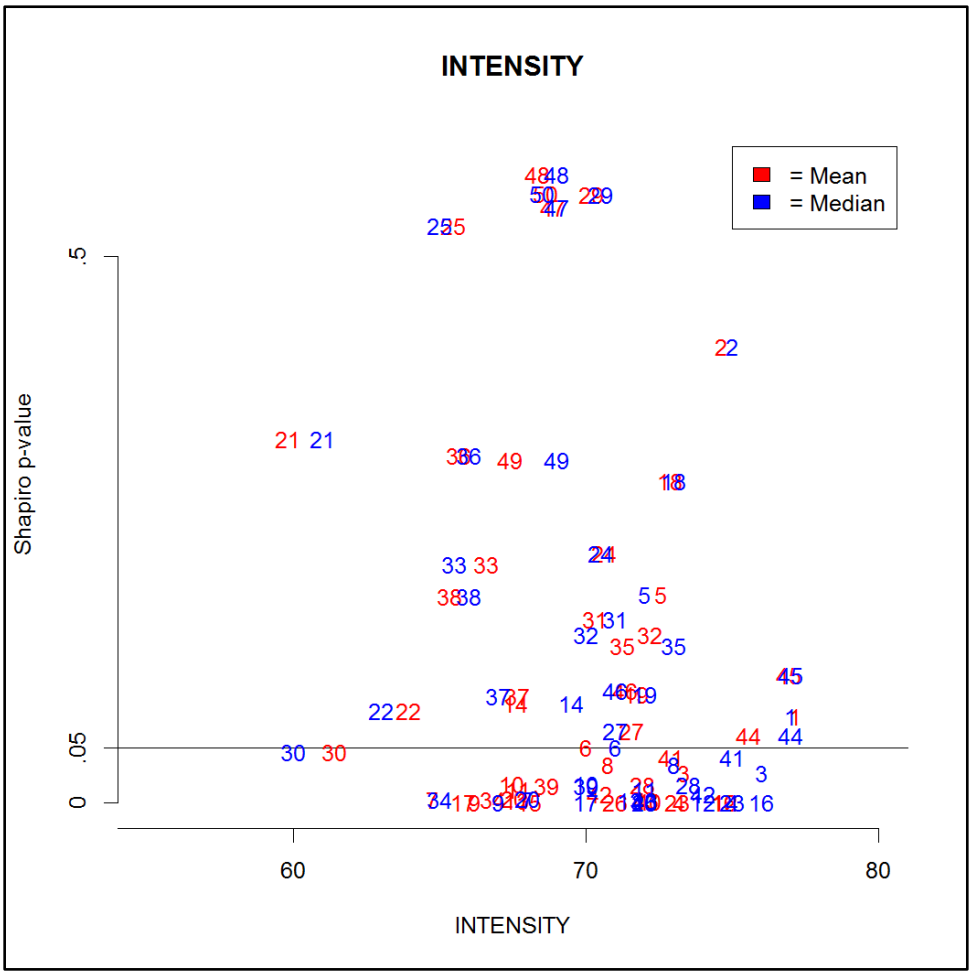

Figure 5.2: A graphical representation of the normality of the intensity of the first 50 vowels of the data. The Shapiro-Wilk p is represented on the y-axis. All those points that fall above the black horizontal line, which represents a p of .05, come from a distribution that can be considered normally distributed. The red numbers represent the mean and the blue numbers represent the median, an alternate measure of central tendency.

Vowel duration and syllable duration were recorded for each UTTERANCE according to accepted methodology (e.g. Wright and Nichols 2009). This methodology employs a visual inspection of speech waveforms and wideband spectrograms using PRAAT phonetic software (Boersma and Weenink 2010) in order to determine and mark the onset and offset of vowels and syllables and measure their durations. The current experiment adopted the methodology employed by Carter (2007) for Spanish diphthongs

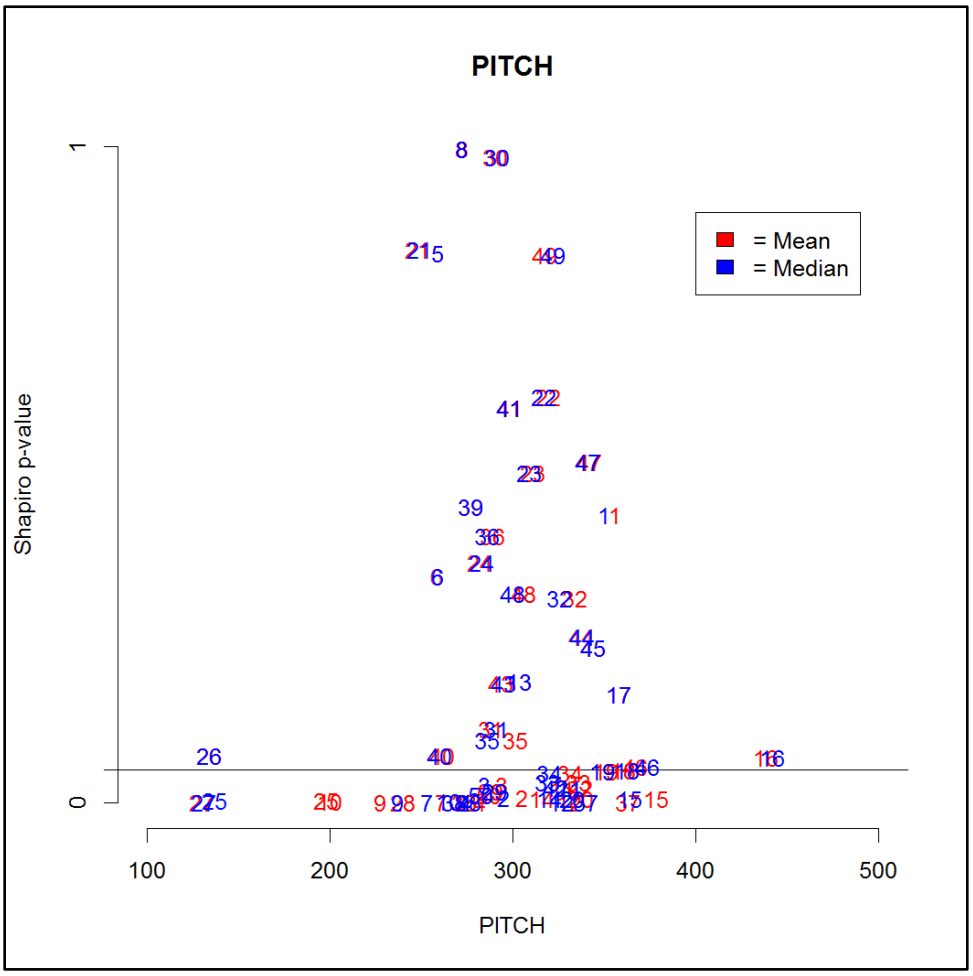

Figure 5.3: A graphical representation of the normality of the pitch of the first 50 vowels of the data. The Shapiro-Wilk p is represented on the y-axis. All those points that fall above the black horizontal line, which represents a p of .05, come from a distribution that can be considered to be normally distributed. The red numbers represent the mean and the blue numbers represent the median, an alternate measure of central tendency.

and considered Spanish diphthongs as a single vowel. In instances of specific individual complications, such as syllable deletion, these were addressed on a case-by-case basis.

The following variables were recorded and calculated for consideration in order to predict the dependent variable, UTTERANCE:

- DURATION_V: a numeric variable providing the length of the vowel in ms;

- DURATION_S: a numeric variable providing the length of the syllable in ms;
- PVIV: the PVI of the duration of the current and the next vowel within the IU (if there was one), computed as in (1);
- PVIS: the PVI of the duration of the current and the next syllable within the IU (if there was one), computed as in (1);
- SDS_INT_PHRASE and SDS_PHON_PHRASE: the standard deviation of the duration of the syllable in the intonational phrase and the phonetic phrase;
- SDV_INT_PHRASE and SDV_PHON_PHRASE: the standard deviation of the duration of the current and the next vowel within the IU (if there was one) and its natural log (after addition of 1 to cope with 0s);
- SDPITCH_INTO_PHRASE and SDPITCH_INT_PHRASE: the standard deviation of the mean pitch across each vowel within the intonational phrase and the phonetic phrase;
- SDPITCH_PAIRWISE: the standard deviation of the mean pitch of each adjacent pair of vowels.
- MAX_PITCH: the maximum pitch of each vowel;
- MIN_PITCH: the minimum pitch of each vowel;
- MEAN_PITCH: the mean pitch of each vowel;
- PVI_PITCH: the PVI of the mean pitch of the current and the next syllable within the utterance, computed as in (2);
- SDINTENSITY_INT_PHRASE and SDINTENSITY_PHON_PHRASE: the standard deviation of the mean intensity across each vowel duration within the intonational phrase and the phonetic phrase;

- PVI_INTENSITY: the PVI of the mean intensity of the current and the next syllable within the utterance, computed as in (3);
- MEAN_INTENSITY: the mean intensity of each vowel;
- SDINTENSITY_PAIRWISE: the standard deviation of the mean intensity of each adjacent pair of vowels.
- SDS_PAIRWISE: the standard deviation of the durations of each adjacent pair of syllables in the utterance;
- SDV_PAIRWISE: the standard deviation of the durations of each adjacent pair of vowel in the UTTERANCE (see SD in **Chapter 3**);
- SDPITCH_PAIRWISE: the standard deviation of the mean pitch of each adjacent pair of vowels.

$$(1) PVI = \frac{|(segmentduration_1 - segmentduration_2)|}{mean(segmentduration_1, segmentduration_2)}$$

$$(2) PVI_{pitch(vowela,vowelB)} = \frac{|(meanpitch_{vowela} - meanpitch_{vowelb})|}{(meanpitch_{vowela} + meanpitch_{vowelb})/2}$$

$$(3) PVI_{intensity(vowela,vowelB)} = \frac{|(meanintensity_{vowela} - meanintensity_{vowelb})|}{(meanintensity_{vowela} + meanintensity_{vowelb})/2}$$

It is worth mentioning some details about some of the variables listed above. Firstly, there are two different ways to measure the standard deviations of segment durations. Some standard deviations are calculated across a certain phonological constituent (as described in the previous section). Those standard deviations of segment duration variables calculated across the intonation and phonological phrase are: SDS_INT_PHRASE, SDS_PHON_PHRASE, SDV_INT_PHRASE, and SDV_PHON_PHRASE. Meanwhile,

SDS_PAIRWISE and SDV_PAIRWISE are calculated in pairwise manner, as in **Chapter 3** (as well as Harris and Gries 2011)[10]. This pairwise calculation is akin to the calculation of the PVI. While neither of these calculations of the standard deviations of segment durations are exactly equivalent to the metric suggested by Ramus, Nespor, and Mehler (1999), which takes the mean of the standard deviations of a speaker's utterances, those variables calculated across the phonological constituents are more similar to that metric in that they consider a series of standard deviations, rather than the standard deviation of two adjacent values.

5.2. Statistical Evaluation and Results

This section will describe two statistical evaluations of the variables mentioned above in order to predict the dependent variable UTTERANCE (*English 1, English 2, Portuguese, Spanish 1, Spanish 2*). The first is an ensemble method, Random Forest, which identifies those variables that are significant predictors of the dependent variable. These predictors were then entered in a maximal multinomial model and an automated model selection process was employed in order to identify those variables most important to the prediction of the dependent variable.

[10] This distinction also exists for the calculation of standard deviation for F0 and intensity. The standard deviation of these features across phonological constituents are SDPitch_Int_Phrase and SDPitch_Int_Phrase and SDIntensity_Int_Phrase and SDIntensity_Phon_Phrase. Meanwhile, SDIntensity_Pairwise and SDPitch_Pairwise are calculated in a pairwise manner. However, metrics related to intensity and pitch are not commonly included in speech rhythm studies. [weird note formatting: the 10 is too large and the hanging indent is different from previous ones]

5.2.1. Random Forest

5.2.1.1. Random Forest Data Treatment

Random Forests are a series of decision trees; each of these trees is based upon a random subset of the available predictors and available data (Breiman 2001). As each tree is "calculated on random subsets of the data, using a subset of randomly restricted and selected predictors for each split in each classification tree…"(Strobl et al. 2008) they are "able to better examine the contribution and behavior that each predictor has, even when one predictor's effect would usually be overshadowed by more significant competitors in simpler models" (Strobl, Malley, and Tutz 2009 as cited in Shih 2011:1).

The current chapter undertook a Random Forest exploration in response to problems of multicollinearity between the variables listed in the section above. As some variables are derived from one another, there were many instances of multicollinearity; this occurs when two or more variables are highly correlated. This can make the coefficients and p-values of the model extremely unstable, making it impossible to determine the cause of the model's predictions, as well as the (directions of) effects of individual predictors. Due to this complication, the results of a multinomial model selection process were not conclusive as to the research questions; there was evidence of multicollinearity amongst the variables (as would be expected, although the procedure for diagnosing and treating multicollinearity in multinomial models is not as yet well defined to the author's knowledge). Random Forests are not susceptible to multicollinearity in the same manner as regression models; "One advantage of RF [Random Forest] is that it can handle this collinearity" (Immitzer, Atzberger, and Koukal 2012:2683). Because the decision trees comprising a Random Forest are generated on a random subset of the

variables and data, a tree at a certain point in the forest may not contain collinear variables.

The current chapter used the function randomforest and method cforest_unbiased from the library party (Hothorn, Hornik, Strobl, and Achim Zeileis 2006). It follows established methodology in experimenting with a variety of settings (e.g. *ntree* and *mtry*[11]) and using these settings with different random seeds (e.g. Strobl, Hothorn, Zeileis 2009). After trying various settings, the optimal settings of *ntree* 1501 and *mtry* 5 were used. It then generated a plot visualizing the conditional importance measure; this has been suggested as an alternate to the permutation importance measure in the case that the predictors may be correlated (Strobl, Hothorn, and Zeileis 2009). The resulting random forest model was 100% accurate in predicting the dependent variable, UTTERANCE. I then generated a plot visualizing the conditional importance measure. The conditional importance measure determines the relative importance of variables in predicting the dependent variable by sub-sampling the data set without replacement. As compared to the permutation importance measure, the conditional importance measure considers the importance of the variables "given the other predictor variables in the model" (Strobl, Hothron, and Zeileis 2009:15). This plot is a visualization of the concept that variables whose variable importance value is greater than the absolute value of the lowest negative-scoring variable are informative predictors of the dependent variable (Strobl, Malley, and Tutz 2009). See Figure 5.4.

[11] *ntree* is a parameter of randomforest that varies the number of trees generated by the random forest and *mtry* specifies the number of independent variables that are sampled at each node for the random forest algorithm.

5.2.1.2. Random Forest Results

As seen in Figure 5.4, 11 of the 22 variables can be considered informative to the dependent variable. Before moving on to a more fine-grained analysis based on these results, a few implications about speech rhythm are worth mentioning. First, this section will address those variables that are not important in the classification of the dependent variables. It will then move on to those variables that are important in the Random Forest.

Recall that one of the most commonly used metrics in the attempted classification of speech rhythms is the PVI. Despite recent studies showing that the PVI alone does not consistently distinguish between languages of different rhythm classes (Loukina, Kochanski, Shih, Keane, and Watson 2009, Harris and Gries 2011), current rhythm studies persist in using the PVI as a metric of speech rhythms (e.g Henriksen 2013). Figure 5.4 suggests that this metric is not an effective predictor for the current data, in addition to the methodological shortcomings described previously, particularly in **Chapter 2**. The PVI of vowel durations, which is used most commonly in previous rhythm literature (here the PVIV, which measures vowel duration variability), does not meet the criteria to be considered a significant predictor of UTTERANCE. Furthermore, the PVIS, which measures syllable duration variability, fares even worse in the presence of other predictors. While the results of **Chapter 3**, as well as the aforementioned literature, would suggest that the PVI would prove a poor classifier of differing rhythms, this evidence of the weak classificatory power of the PVI is especially telling due to the nature of the data; these utterances have been verified via a perception experiment as perceptibly rhythmically different. That is, while other studies have relied upon the assumption that all utterances of a language of one rhythm class differ from all utterances

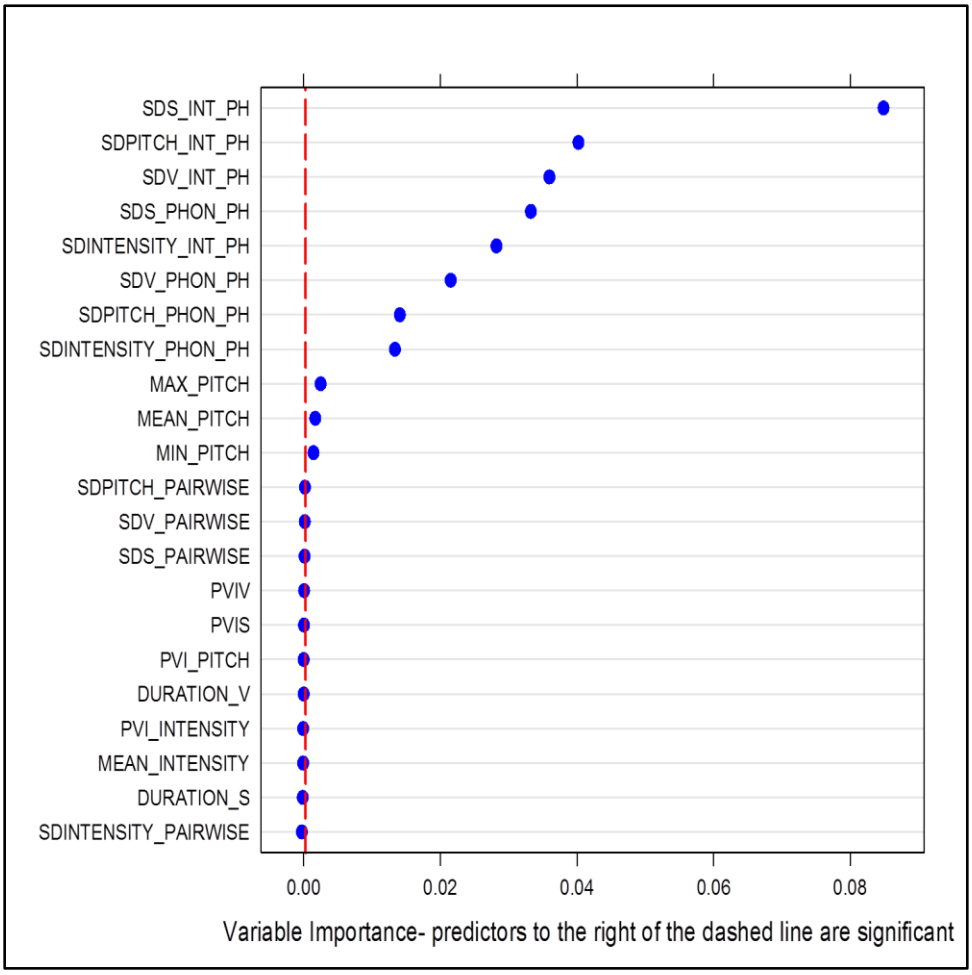

Figure 5.4: Variable importance plot representing the relative importance of the variables in classifying the dependent variable UTTERANCE with a Random Forest ensemble method.

of a language of a different rhythm class, the current study is based on experimental evidence that the utterances used as the dependent variable in the current experiment are perceptibly different in terms of rhythm (based upon the results of **Chapter 4**). The fact that the five levels of UTTERANCE differ from one another in terms of perceived rhythm, yet the PVI fails to distinguish between them in the Random Forest, in addition to Loukina et al. (2009) and Harris and Gries (2011), is ample evidence of the shortcomings of the PVI as a metric of speech rhythms. Note also, that the current chapter does not take

a speaker or speaker type's mean PVI value (the so-called *Mean PVI Method* in **Chapter 2**) and instead considers all the of each utterance's PVI values (the *Raw PVI Method* in **Chapter 2**). However, even with this more statistically sound method of calculating this metric (as well as avoidance of the issue of non-normal distribution of the data), the PVI is not a significant predictor of UTTERANCE.

It is also worth noting that SDV_PAIRWISE, which is akin to SD (and related to SDLOG) from **Chapter 3**, is not a significant classifier of the dependent variables. Instead, the standard deviations of segments defined across the phonological constituents *phonological phrase* and especially *intonational phrase*, prove to be more useful in the Random Forest ensemble. Recall that these variables, particularly SDV_INT_PHRASE and SDV_PHON_PHRASE, are more similar (although certainly not equivalent) to the mean standard deviation of vowel duration used in early rhythm studies (e.g. Ramus, Nespor, and Mehler 1999).

This section will now turn its attention to those variables that are important in the classification of UTTERANCE. Firstly, it is noteworthy that SDS_INT_PHRASE is by far the most important variable in predicting the five levels of UTTERANCE. This means that the most important variable in the ensemble is related to segment duration variability, as has been long suggested in speech rhythm studies. However, the variable that measures the duration variability of the entire syllable fares better than SDS_INT_PHRASE, which measures just the vowel duration variability. Note that these variables related to segment duration variability were significant, while those variables related to segment duration (DURATION_V and DURATION_S) were not significant. This hearkens back to the concept that certain languages privilege the syllable as a prosodic unit (thus lower

SDS_INT_PHRASE), while other languages privilege stress patterns (thus higher SDS_INT_PHRASE); this is in agreement with Dasher and Bolinger's (1982) phonological account of rhythm. However, it is equally important to note that the second most important variable is not related to segment duration variability: SDPITCH_INT_PHRASE. This suggests that one cannot only consider segment duration variability in the discrimination of rhythm classes. In fact, in addition to pitch, variables related to intensity are also included amongst those important in the ensemble (e.g. SDINTENSITY_INT_PHRASE and SDINTENSITY_PHON_PHRASE).

Of the 11 significant variables, 7 of them are related to pitch and intensity, leaving only four related to segment duration variability. This is in agreement with Dauer's (1987) conclusion that simple measures of inter-stress intervals or syllable durations are not effective in determining rhythm class. Instead, it appears that a multidimensional cluster of prosodic cues lead to perceived differences in what linguists commonly call speech rhythms. Even when additional prosodic cues (that is, F0 and intensity) have been normalized and dampened in the speech signal (see **Chapter 4**), they still contribute to perceived differences. The following section will present conclusions to the Random Forest analysis.

5.2.1.3. Random Forest Conclusions and Discussion

Several important conclusions can be drawn from the Random Forest ensemble method described here, although additional exploration and analysis is necessary to fully understand the data and especially to understand the way in which the various utterances relate in terms of speech rhythms (see following section).

An important conclusion in the context of wider rhythm research is that segment duration variability is indeed related to (and in this case, most important to) our perception of speech rhythm distinctions. In this way, researchers have been correct in attempting to identify metrics of segment duration in order to distinguish between languages of different rhythm classes. As mentioned above, it is syllable duration variability, rather than vowel duration variability that proves most important in the current data set (although vowel duration variability does prove relevant as well). This is noteworthy, as the majority of previous speech rhythm research has depended upon vowel duration rather than syllable duration in their metrics. The current results suggest that researchers would be better served in considering the entire syllable instead in their metrics. One explanation for this behavior is that syllables have much more potential variation in their structure, than vowels, which means that rhythmic differences may indeed be correlated with the syllabic structure of a language. This is in agreement with Dasher and Bolinger (1982) who suggested that the phonotactic structure of a language contributes to rhythmic differences; languages with more complex syllable structure tend to have more syllable duration variability and are stress-timed, while languages with simpler syllables have less syllable duration variability and are syllable-timed. Given this suggestion, it is surprising that not more researchers have chosen to consider syllable duration rather than vowel duration in their speech rhythm research.

A second conclusion from the current Random Forest ensemble is that while segment duration variability does play a vital role in speech rhythms, one cannot ignore other prosodic cues. As mentioned, variability in pitch and variability in intensity also lead to perceived differences in the low-pass filtered utterances. As tends to be the case in

linguistics, one cannot focus entirely on one variable or feature to the point of ignoring others. Instead, the entirety of the speech process must be considered.

As mentioned above, while the Random Forest ensemble method is very useful in determining which variables are most useful in distinguishing between the utterances, there is a second step that allows for a more in-depth exploration of this data set, as well as a potentially simplified model (as compared to the Random Forest). Thus, the following section uses the results from the Random Forest as a starting point in choosing variables for a multinomial regression attempting to classify the same dependent variable, UTTERANCE. Several variables identified by the Random Forest ensemble are largely redundant; any variable defined across both the *phonological phrase* and the *intonational phrase* contains much of the similar information, especially given that these two phonological constituents completely overlap at times, and are therefore identical. Furthermore, MAX_PITCH and MIN_PITCH are both closely related to MEAN_PITCH. Thus, the following data analysis attempts to accurately predict the dependent variable with a simplified set of non-redundant variables by choosing the variable with the most predictive power from the groups of redundant variables.

5.2.2. Regression and ctree Analysis

As mentioned, it is the goal of the current section to accurately predict UTTERANCE (*English 1, English 2, Portuguese, Spanish 1, Spanish 2*) with a subset of the metrics identified as significant in the preceding Random Forest analysis. Furthermore, these predictors should be neither redundant nor show evidence of multicollinearity.

As mentioned in *Section 5.1*, there were a total of 22 predictors coded and/or calculated. Of these 22 independent variables, 11 were identified as significant by the Random Forest ensemble in *Section 5.2.1*. Of these, the current analysis started with 5 variables as main effects (as well as considering their two-way interactions) in order to avoid redundancy and multicollinearity. The five main effects were chosen as those effects with the highest predictive power within each five categories. The categories defined and variables selected are shown in Table 5.1.

Category	Variable
syllable duration variability	SDS_INT_PH
vowel duration variability	SDV_INT_PH
pitch variability	SDPITCH_INT_PH
intensity variability	SDINTENSITY_INT_PH
numeric pitch	MAX_PITCH

Table 5.1: five categories defined from the Random Forest ensemble and the most predictive variable belonging to each category.

Thus, the following variables were recorded and calculated for consideration in order to predict the dependent variable, UTTERANCE:

- SDS_INT_PH : the standard deviation of the duration of the syllable in the intonational phrase;

- SDV_INT_PH : the standard deviation of the duration of the vowel in the intonational phrase;
- SDPITCH_INT_PH: the standard deviation of the mean pitch across the vowel in the intonational phrase
- SDINTENSITY_INT_PH: the standard deviation of the mean intensity across each vowel duration within the intonational phrase
- MAX_PITCH: the maximum pitch of each vowel

After selecting these five predictors, a thorough data exploration was undertaken. The purpose of this exploration was to identify potential issues with the data, considering their distribution and the presence of potential outliers. A series of multinomial regressions were performed, using an automated stepwise bidirectional model selection process, stepAIC from the library MASS (Venables and Ripley 2002). This process deletes and adds interactions and variables according to AIC, a criterion that weighs the added complication of adding an additional predictor to the model against the added predictive power of that predictor. These regressions considered a) the complete data set with no transformations; b) two subsets of the data with outliers deleted but no transformations; c) the complete data set with some log and square root transformations to improve the normality of the variables; d) two subsets of the data with outliers deleted and some log and square root transformations to improve the normality of the variables. The data were also examined for evidence of multicollinearity for each of these data explorations. Finally, these same series of data points were examined using the smaller Phonological Phrase, rather than the Intonational Phrase (see *Section 5.1.2.*).

Following this process, three conclusions were reached. Firstly, as suggested by Figure 5.4, the metrics based upon the Intonational Phrase perform better in predicting the dependent variable, as compared to the Phonological Phrase. Thus for the remainder of this chapter, SDS_INT_PHRASE will be referred to simply as SDS, SDINTESITY_INT_PHRASE will be referred to as SDINTENSITY, and SDPITCH_INT_PHRASE will be referred to as SDPITCH. Secondly, the data were optimized when two series of data points were removed. One set of eight data points that showed very high duration variability (SDS>300, SDV>200) were removed. A second set of seven data points that showed very high intensity variability (SDINTENSITY>9) were removed. Both of these sets of data points also showed extremely high pitch variability (SDPITCH>100). Finally, the various regressions showed that three variables were consistently informative in the classification of the dependent variable UTTERANCE: SDS, SDINTENSITY, and SDPITCH were consistently highly significant in predicting UTTERANCE, either as main effects or as interactions. SDV did occasionally participate in a significant interaction in the final model, but as this metric is collinear with SDS, a significant predictor of UTTERANCE. In all models generated, SDS was the more powerful predictor of the two metrics of duration variability; thus SDS was chosen for the following data analysis rather than the standard deviation of vowel duration. The final predictor, MAXPITCH, was not a significant predictor of utterance in any of the models generated.

Given the conclusions above and the categorical nature of the dependent variable, a conditional inference tree (using the package party, Hothorn, Hornik, Strobl, and Zeileis. 2006), was generated. The package's ctree function generates such trees, which are

regression trees that split the dependent variable based on certain values or levels of the independent variables; these trees are based upon a recursive partitioning algorithm that performs significance tests at each stage of the algorithm (Hothorn, Hornik, and Zeileis *no date*). The data set had the outlying data points removed as mentioned in the previous paragraph, but no transformations were performed upon the data. The results of this analysis are presented in the following section.

5.2.2.1. Results and Discussion

Conditional inference trees were generated to predict the dependent variable, UTTERANCE, according to the following three independent variables: SDS, SDPITCH, and SDINTENSITY (all based upon the Intonational Phrase, see above). The resulting model was able to correctly classify UTTERANCE 98.5% of the time, which performs better than a model that classifies the dependent variable as the most frequent level of UTTERANCE 100% of the time ($p < .001$). The results of this data analysis are represented in Figure 5.5 below.

In consideration of the results of the conditional inference trees, the following sections will discuss each of the three predictors, the standard deviation of syllable length, the standard deviation of mean intensity, and the standard deviation of mean pitch. It will first discuss those levels of UTTERANCE that can be predicted based solely upon SDS; it will then consider the predictions that also consider SDINTENSITY and SDPTICH. *Section 5.2.2.1.1* will describe the behavior of the variables seen in Figure 5.5 and the section that follows it will describe the linguistic implications of these effects.

5.2.2.1.1. Conditional inference tress predicting UTTERANCE

Starting with the highest node, node number 1 in Figure 5.5 divides *English 2*, from the other levels of UTTERANCE on the basis of the predictor SDS, the standard deviation of vowel duration. Thus *English 2* is associated with very high syllable duration variability; that is, *English 2* is predicted when SDS values are higher than 163. The other utterance associated with high syllable duration variability is *Portuguese*, as seen from the split below node 6. When SDS is between 107 and 163, *Portuguese* is predicted.

The other two utterances that are predicted based solely upon SDS are those utterances associated with extremely low syllable duration variability. *English 1* and, to a lesser degree, *Portuguese* are predicted by the conditional inference trees when the standard deviation of syllable duration falls below 65. *Spanish 2* is also predicted when SDS is quite low, between 65 and 80.

For the area of intermediate syllable duration variability, when SDS is between 32 and 107, SDINTENSITY and SDPITCH interact with SDS in order to predict UTTERANCE. Node 7 splits the levels of UTTERANCE into two groups based upon SDINTENSITY. *English 1* is associated with greater variability in intensity as compared to Portuguese. Meanwhile *Spanish 1* can occur with both high and low levels of SDINTENSITY. Those *Spanish 1* phrases that are pronounced with less variability in pitch also display less variability in intensity, and Spanish1 phrases with greater variability in intensity also display more variability in syllable duration variability. Meanwhile, *Portuguese* is predicted with greater SDPITCH and *English 1* is predicted as having less syllable duration variability (as seen above). The following section will discuss the linguistic implications of these effects.

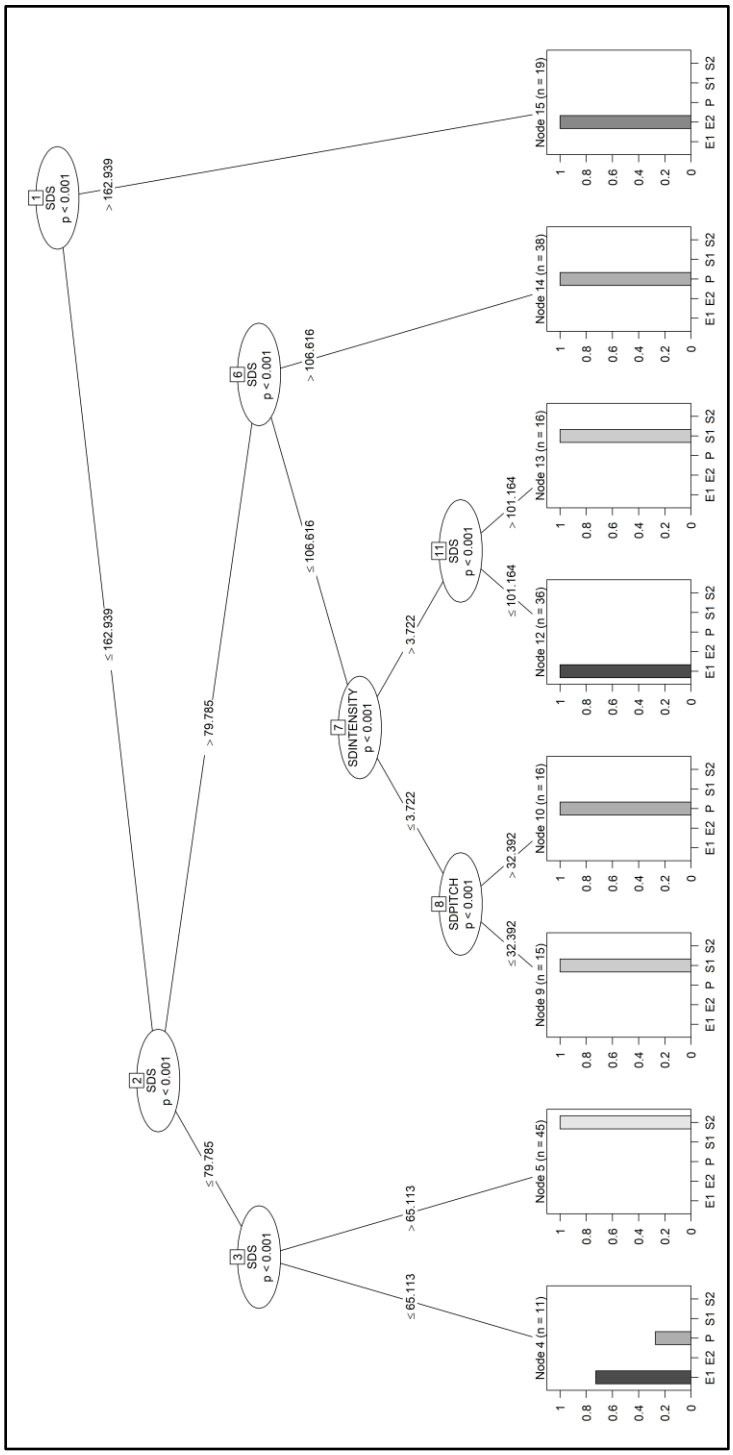

Figure 5.5: A visual representation of the conditional inference trees to predict the dependent variable UTTERANCE.

5.2.2.1.2. Linguistic Implications

This section will consider the implications of the conditional inference trees. First the English utterances are discussed. Portuguese is addressed next and the Spanish utterances follow.

Traditional rhythm typology would suggest that the English utterances would have high variability in syllable duration, as does *English 2*, which is predicted when SDS is greater than 163. However, notice that the split in node 3 associates very low syllable duration variability with *English 1*. This is exactly the opposite of traditional rhythm class typology, as the utterance is predicted with extremely low syllable duration variability. Keep in mind that both of the utterances are from the same speaker. The fact that these two utterances do not behave in a uniform manner is in agreement with Loukina, Kochanski, Shih, Keane, and Watson (2009), who conclude that while rhythms vary between languages, they also vary within languages. Thus, it is not particularly surprising to find two utterances of the same language from the same speaker occupying different areas of syllable duration variability.

Portuguese is associated with both relatively high syllable duration variability, when SDS is greater than 107 but less than 163, and also with very low levels of syllable duration variability, also the prediction is less strong. Recall that Frota and Vigário (2001) concluded that Portuguese has an intermediate rhythm class. In this sense, Portuguese follows the traditional rhythm class typology by displaying some high syllable duration variability and some low syllable duration variability. Notice also that Portuguese is predicted when syllable duration variability is intermediate to low, intensity variability is low, but pitch variability is high. These predictions could be indicative of vowel deletion

in unstressed syllables. Increased intensity has been shown to be a correlate of stress in European Portuguese (Ferreira 2008:11), and unstressed vowels have been shown to have a reduced system (Frota and Vigário 2001). Perhaps those vowels that are unstressed, and thus not very variable in terms of intensity, also show less variability in terms of duration, as they are uniformly short. At the same time, pitch variability remains relatively high, suggesting that unstressed vowels may still maintain a similarly level of F0 variability as do stressed vowels (this increased pitch variability may also be associated with the distinction between plastic and non-plastic languages in the coding of new and given information, see paragraph below). This potential explanation is only a speculation at this point; especially given that vowel duration did not factor into the model as a significant predictor (see Random Forest analysis above). However, it does provide an explanation for the behavior of Portuguese in Figure 5.6. See Figure 5.7 for an example of vowel deletion in Portuguese from the data.

In terms of SDPITCH, *Spanish 1* shows low pitch variability and *Portuguese* shows high pitch variability. One explanation for the behavior of these languages is the distinction between plastic and non-plastic languages in information structure. Languages such as English and Dutch are traditionally considered *plastic languages*; plastic languages tend to use pitch excursions to signal new information (equivalent to narrow focus) in a narrative. Meanwhile Spanish, which is considered a *non-plastic language*, uses word order instead (Zubizarreta and Nava 2010; Swerts, Krahmer, and Avesani 2002). Much like the case of speech rhythms, the status of Portuguese as a plastic or non-plastic language is less clearly defined. As Romance languages such as Spanish and Italian are typically considered to be non-plastic languages (Zubizarreta and Nava 2010;

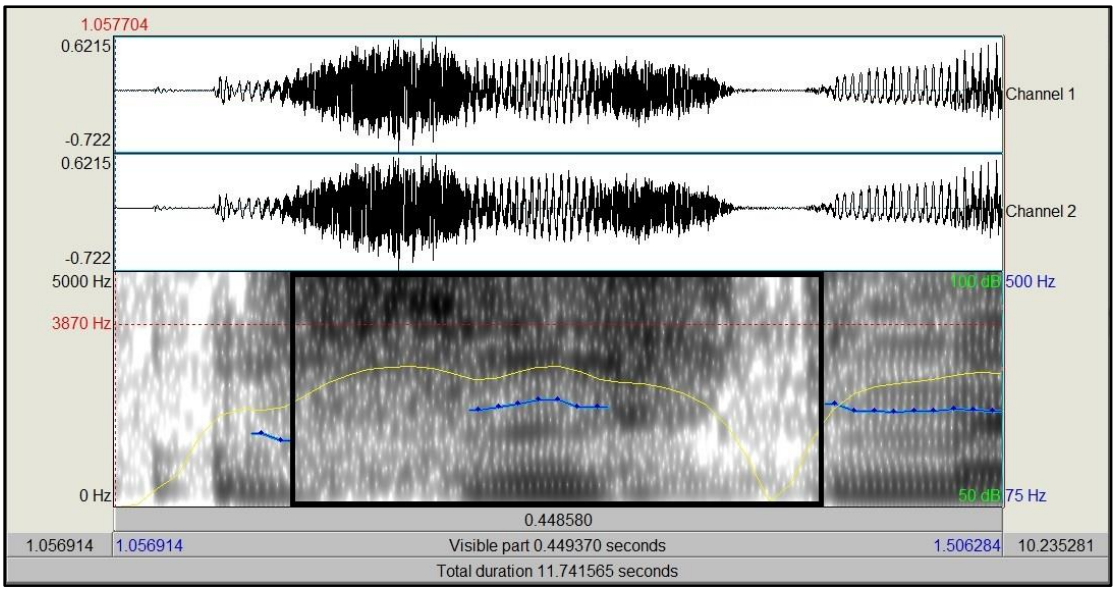

Figure 5.6: Vowel deletion in unstressed position in Portuguese. The word in the black box is *susto* /sˈuʃtu/. However, the unstressed vowel has been deleted in this case: /sˈuʃt/

Swerts, Krahmer, and Avesani 2002), one would expect that Portuguese would also be a non-plastic language. However, even non-plastic languages use some tone in the signaling of narrow focus (Face 2005). In the case of Portuguese, Frota (1997) shows evidence for the use of tone in European Portuguese for narrow as opposed to broad focus. While previous literature does not specify whether Portuguese would more or less plastic than Spanish, Face (2005) suggests that Italian, at least, is more plastic than Spanish. In the case of Portuguese, SDPITCH in Figure 5.5 provides anecdotal evidence that some utterances in Portuguese are more plastic in terms of use of pitch variation in information structure, which is in agreement with Frota (1997). The current study did not, of course, control for new or given information, and this evidence is based on extremely sparse data. However, this does provide a partial explanation why some Spanish uses less variation in pitch as compared to Portuguese. In Figure 5.7 which is a comparison of the use of tone in new information in *Spanish 1* and *Portuguese*, the Portuguese tone contour for new

information is flatter (and thus less variable) than the Spanish contour for new information .

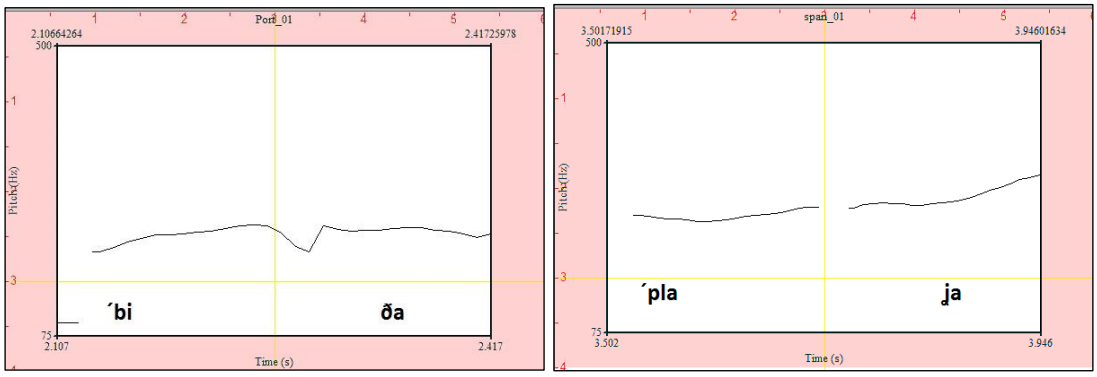

Figure 5.7: A comparison of the pitch contours for new information in Portuguese (left panel) and Spanish (right panel) from the current data set. The Portuguese word *vida* is on the left and the Spanish word *playa* is on the right. Both are the first mention of these words in the dialogue.

The utterance *Spanish 2* follows traditional rhythm class distinctions by displaying low duration variability, as would be expected of a syllable-timed language. Meanwhile, *Spanish 1* is associated with a low to intermediate level of syllable duration variability, although predictions for this level of UTTERANCE are affected by variability in intensity and pitch. In fact, *Spanish 1* is the only level of UTTERANCE that is affected by all three variables, showing lower variability in intensity and pitch simultaneously and greater variability in intensity and syllable duration variability simultaneously. It is not surprising that these prosodic variables work in conjunction. Duration, pitch, and intensity have all been shown to be correlates of lexical stress for instance (e.g. Fry 1955, 1958), so it follows that these features would also be present in variation in syllabic rhythm. In fact, the use of these cues as a correlate of lexical stress provide an explanation for the behavior of these variables. The prediction for *Spanish 1* under nodes 7 and 8 could be unstressed syllables, which would have low pitch variability and low intensity variability,

as seen in Figure 5.5. Meanwhile, the predictions for *Spanish 1* that have high intensity also have higher syllable duration variability. This could be indicative of lexical stress, with greater intensity and duration, leading to higher standard deviation of syllable duration.

The conditional inference trees show some adherence to traditional rhythm class and language typologies, while at other points the data do not follow these typologies. In terms of rhythm, Portuguese and Spanish most closely follow rhythm typologies, while the two English utterances do not behave in a uniform manner; *English 2* follows traditional speech rhythm class distinctions by displaying high syllable duration variability while *English 1* behaves in exactly the opposite manner, displaying extremely low syllable duration variability. This suggests the general conclusion that in a general sense speech rhythm typologies may hold true, but speaker performance creates a great deal of variation, making it very difficult to assess language-wide rhythmic typology on the basis of a few speakers. An additional conclusion of this interaction is that, in addition to the varied behavior of vowel segment duration variability, it is even harder to predict the behavior of such variables in consideration of additional prosodic cues such as intensity and pitch. Put simply, it is difficult to tease apart intensity, pitch, and rhythm as they all work in conjunction for discursive purposes.

5.2.1.3 General Discussion

The conclusions mentioned in the discussions above all point to a few practical implications to the rhythmic behavior of the three languages that provide the utterances in the current data set and the study of speech rhythms at large. At the risk of repetition, the most apparent fact related to the behavior of these languages is that although languages in

the broad sense appear to adhere loosely to traditionally defined rhythm typologies, the rhythmic variation that occurs in individual performance of single individuals (as well as the variation between speakers of the same language, e.g. **Chapter 2** and **Chapter 3**) makes it hard to distinguish rhythm typology based solely upon a limited amount of speakers or sufficiently large sets of data. This suggests that the automated methodology pioneered by Loukina, Kochanski, Shih, Keane, and Watson (2009) provides a promising route for further investigation into these matters.

5.3 Post Hoc Analyses

Following the analysis described in this chapter, there still remained several questions to investigate via *post hoc* analysis. The current section investigates two questions. The first issue to be investigated is whether there is any correlation between correlates of duration variability, pitch, intensity, and/or segment duration with corpus-based frequency analysis; as seen in **Chapter 3**, some measures of duration variability interact with corpus-based frequency variables. Thus, it its necessary to consider the role of frequency in the current data. The second issue investigated is if there is any correlation between syllable structure and the various utterances. The conditional inference trees analysis concluded that speaker performance made generalizations about speech rhythm classes difficult; this is especially true given that additional prosodic cues such as F0 and intensity work in conjunction with vowel duration variability. However, in a broad sense, the data do appear to reveal consistency between traditional rhythm typologies and the current data. Dasher and Bolinger (1982) suggested that perceived rhythmic differences are a product of phonological properties of a language. In order to further investigate this,

the current chapter considers the syllabic structure of the utterances that comprise the current data in order to assess this possibility. The remainder of this section reviews these two issues via linear models.

5.3.1. Corpus-based Frequency Variables

As mentioned in **Chapter 3**, certain phonological variables have been shown to vary with corpus-based frequency effects (e.g. Bell et al. 2009; Raymond and Brown 2012). Further, the results of **Chapter 3** show that these frequency effects extend to some correlates of vowel duration variability; specifically, the PVI (of vowel durations) and the (logged) standard deviation of vowel durations behave differently with lemma frequency. In consideration of these facts, it is necessary to consider frequency effects in the current data. However, the dependent variable of the data explorations described in the current chapter was determined according to stimuli from which no individual lexical item was recoverable. For this reason, it would be unsound to consider these frequency effects in predicting the dependent variable used in the previous analyses. However, a post hoc analysis permits one to investigate whether the predictors identified as significant by the Random Forest vary with word frequency. Thus, the correlation strength between each of the highest ranking variables (according to the Random Forest analysis) representing segment duration variability, pitch, and intensity were investigate for their correlation with the following variables, as well as syllable duration (DURATION_S):

- TOKEN_PM_LOG: the log of the frequency of the word form per million (after addition of 1 to cope with 0's) in which the segment occurred in the Corpus del

Español- 20th Century Files (Davies 2002-), Corpus do Português- 20th Century Files (Davies and Ferreira 2006-), Corpus of Historical American English- 20th Century Files (Davies 2010-);

- LEMMA_PM_LOG: the log of the frequency of the lemma per million (after addition of 1 to cope with 0's)in which the segment occurred in the Corpus del Español- 20th Century Files (Davies 2002-), Corpus do Português- 20th Century Files (Davies and Ferreira 2006-), Corpus of Historical American English- 20th Century Files (Davies 2010-);

The highest-ranking variables representing segment duration variability, pitch, and intensity were SDS, SDPITCH, SDINTENSITY (recall that the full name of these variables were SDS_INT_PH, SDPITCH_INT_PH, and SDINTENSITY_INT_PH). DURATION_S was also included as a correlate for segment duration (as opposed to duration variability). A preliminary exploration of the correlation between these variables and TOKEN_PM_LOG and LEMMA_PM_LOG revealed that both of these frequency variables behaved in a very similar manner. As they both represent different metrics of corpus-based word frequency, the current analysis will only discuss TOKEN_PM_LOG to avoid redundancy.

A Pearson's product-moment correlation test revealed no correlation between TOKEN_PM_LOG and SDS_INT_PH ($t = -0.05$, $df = 209$, $p = 0.9$, $r = -0.0034$) or between TOKEN_PM_LOG and SDINTENSITY_INT_PH ($t = -1.47$, $df = 209$, $p = 0.14$, $r = -0.1012$). The correlation test did reveal a significant correlation between TOKEN_PM_LOG and SDPITCH_INT_PH ($t = -2.2304$, $df = 209$, $p = 0.02679$, $r = -$

0.1524). There was also a significant correlation between TOKEN_PM_LOG and DURATION_S (t = -3.60, df = 209, p < 0.001, cor = -0.2415). The following sections will first consider the correlation between DURATION_S and TOKEN_PM_LOG, and then the correlation between SDPITCH_INT_PH and TOKEN_PM_LOG.

5.3.1.1. Frequency and Syllable Duration

There is a significant correlation between token frequency and the syllable duration in the intonational phrase, but this simple correlation does not show if a) stress affects this effect or b) if this effect varies across languages (or utterances).

To further explore this possibility, a linear model was generated consideration in order to predict the dependent variable, DURATION_S with the following independent variables:

- TOKEN_PM : the log of the frequency of the word form per million (after addition of 1 to cope with 0's) in which the segment occurred in the Corpus del Español- 20th Century Files (Davies 2002-), Corpus do Português- 20th Century Files (Davies and Ferreira 2006-), Corpus of Historical American English- 20th Century Files (Davies 2010-);
- STRESS : a binary variable that describes whether the segment from which the metrics are derived has lexical stress (*yes* or *no*);
- UTTERANCE: the UTTERANCE from which the segment is derived; note that this has the original six levels *English 1*, *English 2*, *Portuguese 1*, *Portuguese 2*, *Spanish 1*, *Spanish 2*;

A maximal model was generated with all three predictors and their two-way interactions. An automatic model selection process was employed using the function stepAIC from the library MASS (Venables and Ripley 2002). As mentioned, this process adds and removes interactions and independent variables in order to minimize AIC, which weighs additional model complexity versus predictive improvement of the model caused by each additional predictor. The final resulting model was highly significant ($p < 0.001$) but only explained a small amount of the variance in the model (adjusted R-squared = 0.1975). It featured two significant main effects: UTTERANCE ($p = 0.000202$) and TOKEN_PM ($p = 0.001105$). It also featured one significant interaction: STRESS : UTTERANCE ($p = 0.002143$). The following two paragraphs will discuss first TOKEN_PM (the only significant main effect that does not participate in the significant interaction) and then the interaction STRESS : UTTERANCE.

Figure 5.8[12] shows the main effect of token frequency on syllable durations. It is clear that, in the present data, highly frequent words are pronounced with far shorter syllables, while less frequent words are pronounced more slowly, leading to longer syllable durations. This makes sense from the perspective of both production and perception. Less familiar words may be pronounced more slowly as the speaker is less familiar with these words. However, keep in mind that all 3 speakers who contributed these utterances were native monolingual speakers of their respective languages. Given their familiarity with the language, it may be that their careful pronunciation of less frequent words was intended to ease the processing load for the intended audience. This is

[12] Figures 5.7, 5.8, 5.9, and 5.10 were generated using the effects package (Fox 2014) for R (R Development Core Team 2013).

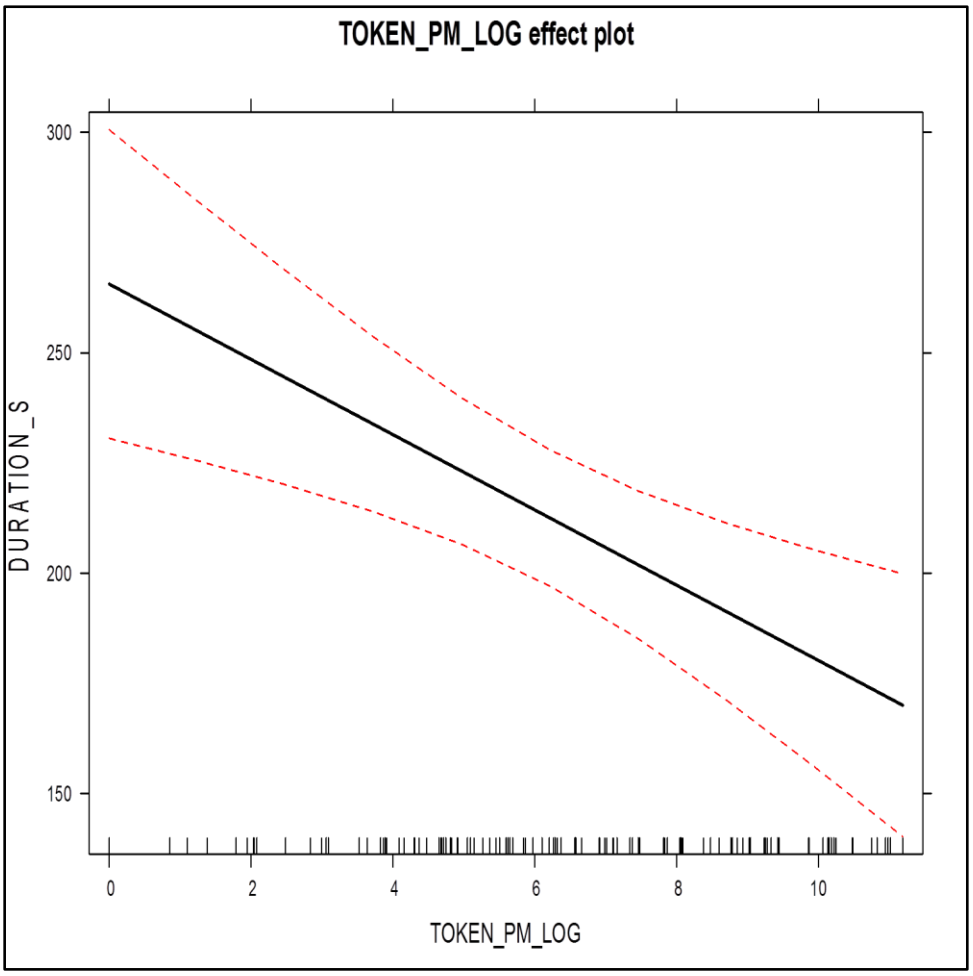

Figure 5.8: the main effect of Log Token Frequency per Million in predicting the duration of the syllables in a post hoc analysis. Syllable durations are represented on the y-axis. (Log) Token frequency per million words is represented on the x-axis, with highly frequent words represented to the right side of the graph.

perhaps even more likely the case given that a) this effect does not vary across the three languages (or six utterances) represented and b) the semi-directed interviews of the Spanish portions of the corpus were conducted by a non-native speaker of Spanish. This provides a potential alternate explanation to the conclusions of **Chapter 3**, where frequency effects on pronunciation were attributed to speaker aptitude. However, given that the speaker groups of **Chapter 3** (monolingual Spanish versus bilingual Spanish) were different than those of the current chapter, these results do not contradict those of

Chapter 3. In fact, it is possible that both speaker aptitude and concerns for listener perception were both at play in the currently observed effects.

Although the interaction STRESS : UTTERANCE was not informative as the main inquiry of the current post hoc analysis, as it does not involve corpus-based frequency effects, it is worth examining the interaction in order to more fully understand the data set. A few trends can be observed in Figure 5.9; firstly it is observable that the utterances differ between languages in some cases and within languages in other cases,

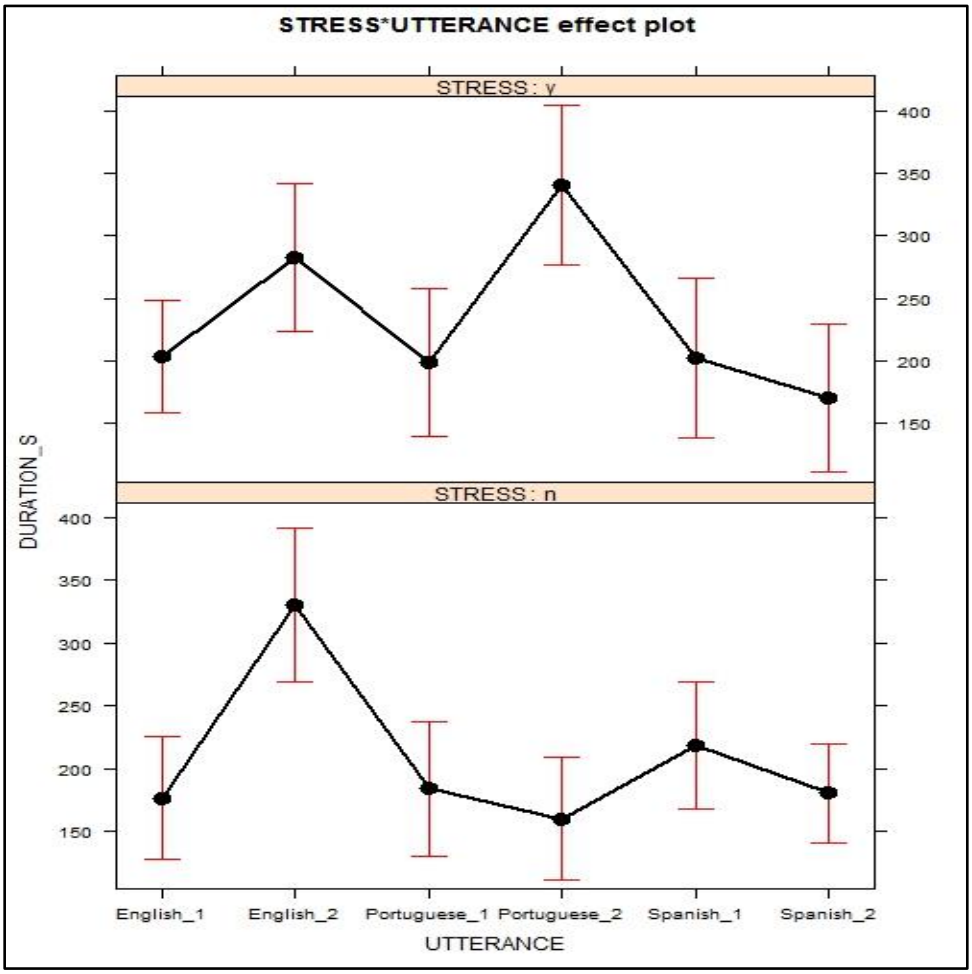

Figure 5.9: The interaction STRESS : UTTERANCE in prediction the dependent variable syllable duration (DURATION_S) in a post hoc analysis. The syllable durations are represented on the y-axis; the left panel represents syllables without lexical stress, and the right panel represents stressed syllables.

and these changes differ in the case of stressed syllables. Perhaps the most counterintuitive trend observable is that of *English 2*, where unstressed syllables are longer than stressed syllables. Longer vowel duration is generally considered a correlate of lexical stress in languages where duration is not phonological (e.g. Fry 1958), as is the case in English, Spanish, and Portuguese, so one would expect the opposite. However, the syllable durations of *English 2* seem to be quite long in general, so it is difficult to make generalizations on the case of this limited data. In terms of vowel reduction of unstressed vowels, there does not seem to be a consistent language-based typology observable in the current data (of course, this effect examines syllable, rather than vowel duration). Recall that Dasher and Bolinger (1982) suggested that syllable-time languages display less vowel reduction as compared to stress-timed languages. This concept is not reinforced by the current data set, as the syllable durations do not vary between stressed and unstressed syllables in a consistent manner when grouped according to language. In general, this interaction further illustrates the general conclusion of the current chapter that there the production of individual speakers features a large amount of prosodic variation, even between two different phrases in the same conversation. This may vary further between stressed and unstressed syllables as well.

5.3.1.2. Frequency and Pitch

As in the previous section, the current analysis uses a multifactorial model to investigate the manner in which pitch variability varies with token frequency. This affords a perspective of how stress affects this effect and its variation across languages (or

utterances). A linear model was generated consideration in order to predict the dependent variable, SDPITCH_INT_PH with the following independent variables:

- TOKEN_PM : the log of the frequency of the word form per million (after addition of 1 to cope with 0's) in which the segment occurred in the Corpus del Español- 20th Century Files (Davies 2002-), Corpus do Português- 20th Century Files (Davies and Ferreira 2006-), Corpus of Historical American English- 20th Century Files (Davies 2010-);
- STRESS : a binomial variable that describes whether the segment from which the metrics are derived has lexical stess (*yes* or *no*);
- UTTERANCE: the UTTERANCE from which the segment is derived; note that this has the original six levels *English 1*, *English 2*, *Portuguese 1*, *Portuguese 2*, *Spanish 1*, *Spanish 2*;

As in the previous section, a maximal model was generated with all four predictors and their two-way interactions. The same automatic model selection process was employed (stepAIC from the library MASS (Venables and Ripley 2002)). The final resulting model was highly significant with a p = < 0.001). However, it only explained a small percentage of the variance in the model (adjusted R-squared = 0.2409). It featured two significant main effects: the highly significant UTTERANCE ($p < 0.001$) and the marginally significant TOKEN_PM ($p = 0.05244$). Although this represents only marginal significance level, it is beneficial to discuss this effect in the context of the linear model (rather than as a simple correlation between SDPITCH_INT_PH and TOKEN_PM), as it

keeps the other predictors at a baseline level, allowing us to observe the behavior of the corpus-based frequency effects in isolation. For this reason, the following two paragraphs will first address the correlation between SDPITCH_INT_PH and TOKEN_PM; it will then discuss SDPITCH_INT_PH and UTTERANCE.

As Figure 5.10 shows, low frequency words are pronounced with far more pitch excursions as compared to high frequency words. This effect is strikingly similar to that of DURATION_S. It appears that pitch movement is featured more prominently in the

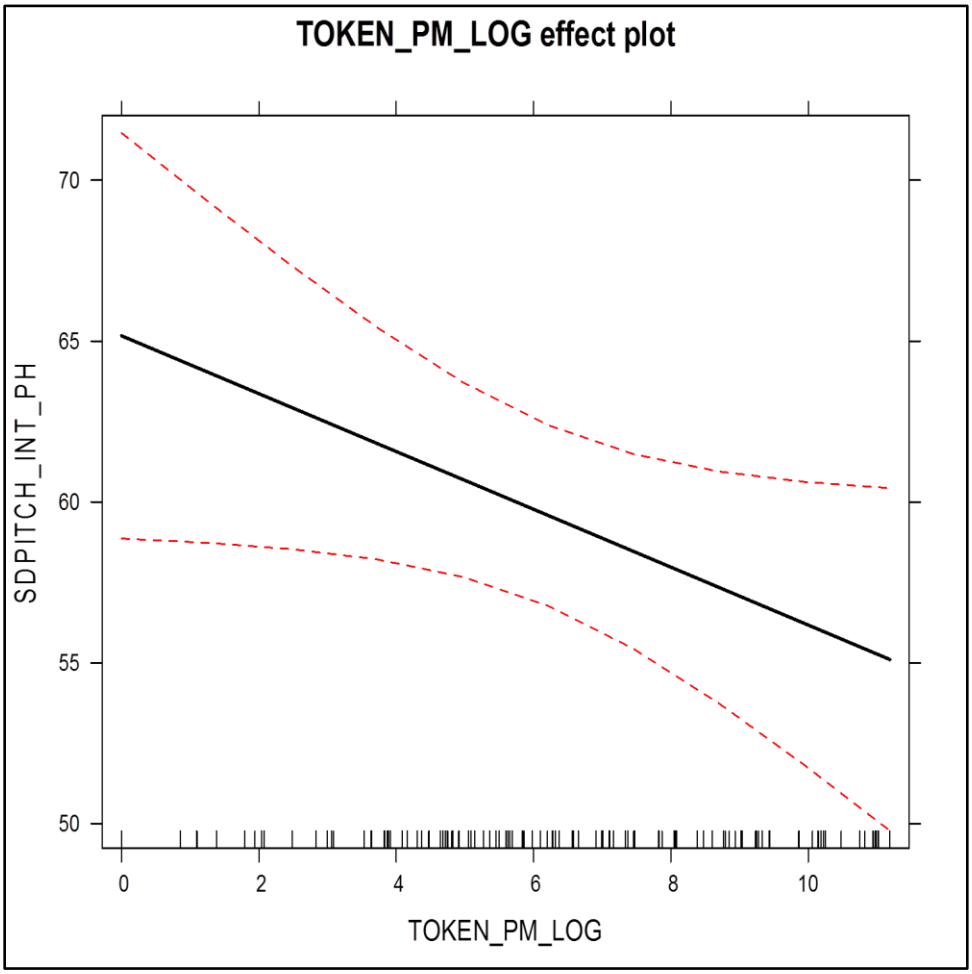

Figure 5.10: the main effect of Log Tokens per Million in predicting the standard deviation of pitch within the intonational phrase. The variability of mean pitch is represented on the y-axis, and the token frequency is represented on the x-axis, with higher frequency words more to the right.

presence of longer durations. This is not surprising, as pitch and duration have been shown to work in conjunction in certain prosodic environments; for instance, both vowel duration and pitch have been shown to increase as a correlate of lexical stress (e.g. Fry 1958). However, these two effects, while varying with corpus-based frequencies, do not vary between stressed and unstressed syllables (in the current model). It is also interesting to note that in the two previous analyses, syllable duration and pitch movement are both present. However, the correlate of intensity variability (SD_INTENSITY_INT_PH) was not significantly correlated with the frequency effects. In terms of stress, it has been suggested that intensity is a less reliable correlate as compared to segment duration and F0; intensity is "generally considered a weak cue in the perception of linguistic stress" (Sluijter and van Heuven 1996:2471). The current post hoc analyses are in agreement with this general conclusion[13].

Figure 5.11 makes it clear that the variability of mean pitch varies according to the utterances. As was the case with STRESS : UTTERANCE, this effect is not informative to the main query of this analysis, namely the variance of certain prosodic elements with corpus-based frequency effects. This being said, the trends observable in this variable are similar the conclusions of the interaction STRESS : UTTERANCE from the previous analysis. Namely, pitch excursions vary both between speakers and within speakers in the current data. It is also interesting to note that the high syllable durations observed in English 2 in the previous analysis appear to coincide with more pitch excursions observed in the current analysis.

[13] As a reminder, the correlates of pitch (F0) and intenesity are based upon the low-pass filtered signal, while the durations related to segment duration (here DURATION_S) are taken from the full speech signal.

5.3.2. Syllabic Structure

As mentioned in the introduction to the post hoc analysis, while variation in speaker production make broad generalizations about rhythm class difficult according to such limited data, there still does seem to be some consistency between traditional rhythmic typology and the results of the current chapter in certain environments. Recall that Dasher and Bolinger (1982) suggested that speech rhythm differences can be attributed to phonological phenomena. The authors suggested that vowel reduction of unstressed

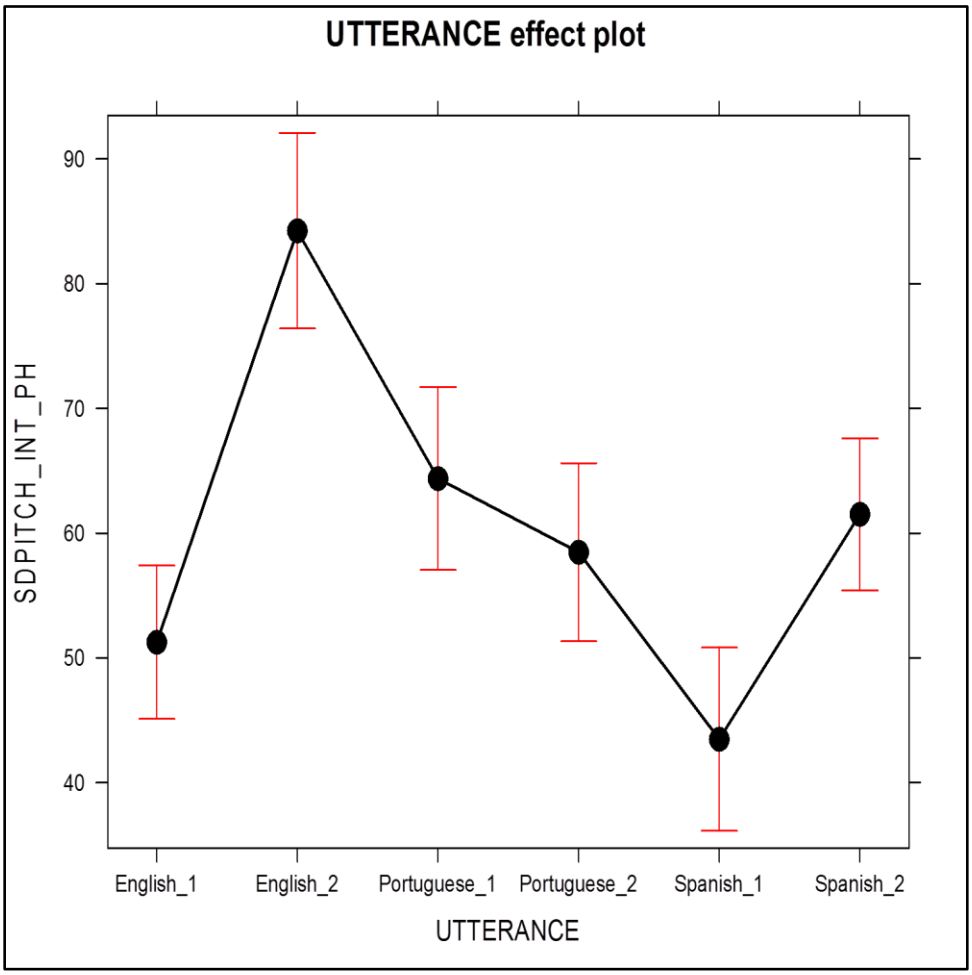

Figure 5.11: The standard deviation of mean pitch in the intonational phrase divided according to the six original utterances that comprise this data set. The variability of mean pitch is represented on the y-axis, with higher variability being higher on the axis.

vowels is correlated with stress-timed languages. However, the results of the previous analysis do not seem to reflect this concept, although the data set is admittedly limited (see STRESS : UTTERANCE, Figure 5.9). The other feature that Dasher and Bolinger (1982) attribute to stress-timed languages is more complex syllable structure. Although a more encompassing study of cross-linguistic variation in syllabic structure would be the subject of a large corpus study, the current dissertation undertook a post hoc analysis of syllabic structure in order to examine whether Dasher and Bolinger's (1982) concept holds true in the current data.

In order to assess the syllabic structure of the language, the current data were coded according to the number of letters in each syllable. As this variable is somewhat susceptible to spelling conventions in the various languages, diphthongs and consonant clusters comprising a single phoneme were coded as a single letter, rather than two. A multinomial model was generated to predict the dependent variable UTTERANCE(*English 1*, *English 2*, *Portuguese*, *Spanish 1*, *Spanish 2*) with the dependent variable LETTERS_SYLLABLE. The resulting model was highly significant ($p < 0.001$). However, the model only performed intermediately well in classifying UTTERANCE. It correctly classified the UTTERANCE from which the syllable was derived 32% of the time (keep in mind that this is a multinomial model with 5 levels). This is significantly higher than a baseline model that randomly chooses the UTTERANCE ($p < 0.001$). The following paragraph will consider the behavior of LETTERS_SYLLABLE in the prediction of UTTERANCE.

Figure 5.12 shows that, unlike in the previous analyses, the utterances group according to language. This, in itself, is not surprising. Each pair of utterances represents the same language, so it would follow that these languages behave as such in terms of syllable structure. However, this effect is still interesting on two counts. Firstly, given that there was so much variation in the production of these utterances, it is worth

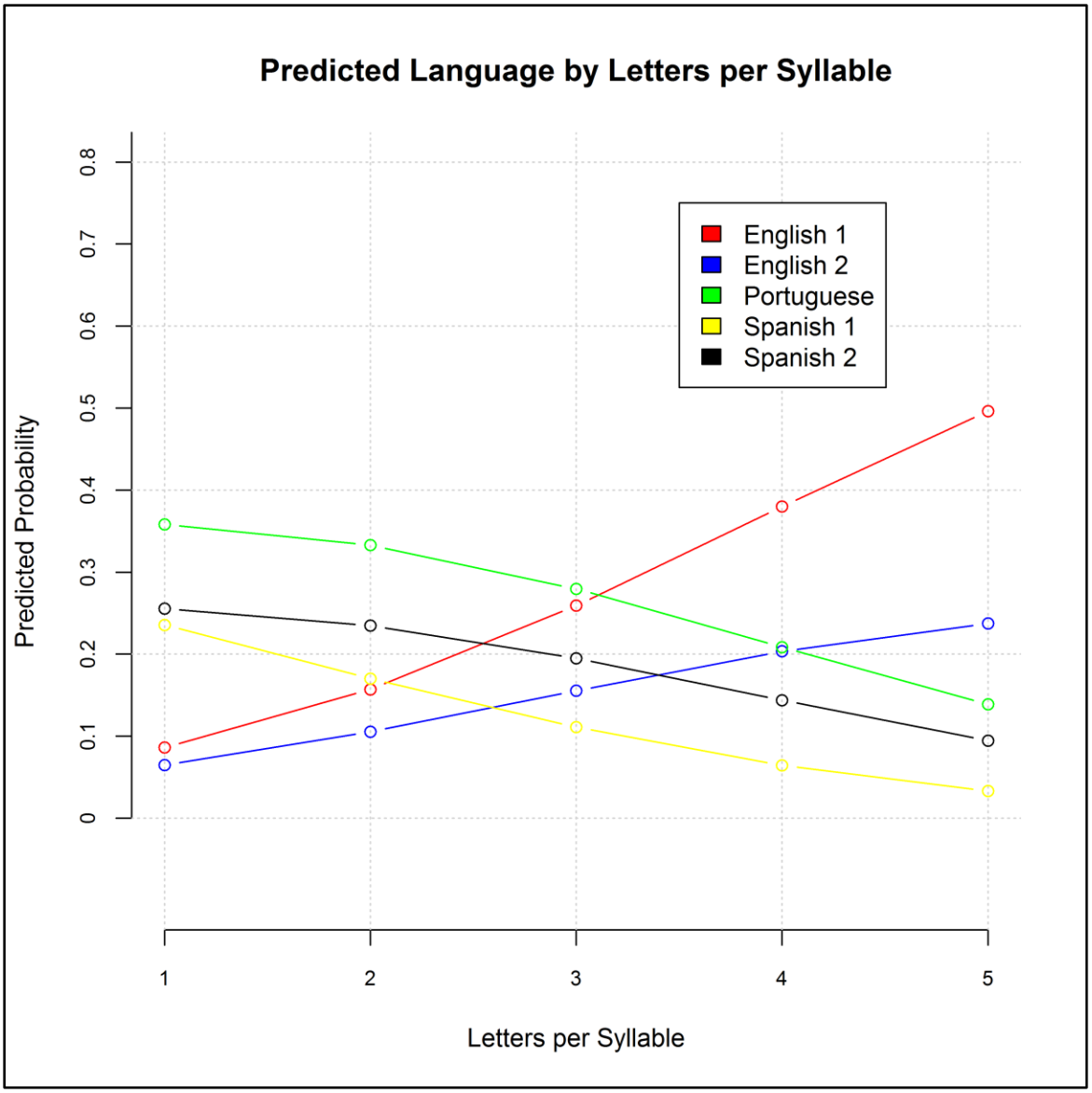

Figure 5.12: The results of a multinomial regression model attempting to predict each UTTERANCE according to the number of letters per syllable. The predicted probability of each UTTERANCE is

represented on the y-axis; the utterances themselves are coded according to the color of the line/dots representing them. Letters per syllable is represented on the x-axis.

noting that in terms of syllable structure, the utterances are quite similar within languages. Secondly, and more importantly, the results of this model are more in line with traditional speech rhythm typology. Consider the speech rhythm continuum: As English is a prototypical stress-timed language, it would be associated with complex syllable types (Dasher and Bolinger 1982). This is exactly what the data reflect; English utterances have a high predicted probability when the syllable is longer and a lower predicted probability when the syllable is shorter. The Romance languages, meanwhile, group together. Spanish behaves in the manner one would expect from a syllable-timed language, with stronger predictions in the simple syllable types and weaker predictions in more complex syllable types. Portuguese, follows the same linear trend as the two Spanish utterances, although it has stronger predictions in both areas. This is due to the fact that the Portuguese UTTERANCE is comprised of two utterances combined into one according to the results of **Chapter 4**. As it has more data points as compared to the other levels of UTTERANCE it will have overall stronger predictions (*Portuguese* has 64 segments, while *English 1* has 44, *English 2* has 27, *Spanish 1* has 31, and *Spanish 2* has 45). In order to a) get a more fine-grained perspective of the behavior of the Portuguese utterances in the data and b) get a more fine-grained perspective of the data in terms of language rhythmic typology, a second data exploration was undertaken. In this analysis, the 6 original utterances (*English 1, English 2, Portuguese 1, Portuguese 2, Spanish 1, Spanish 2*) were used as the levels of the dependent variable UTTERANCE, rather than the 5 used in the original multinomial analysis of the current chapter.

The variable LETTERS_SYLLABLE was entered into a multinomial regression to predict UTTERANCE (once again with 6 levels). The resulting model was highly significant ($p = 0.002251689$) but only performed intermediately well in classifying the 6 levels of UTTERANCE; it predicted the correct UTTERANCE 28% of the time, which was significantly better than a model that randomly chooses the dependent variable ($p < 0.001$). The resulting effect of LETTERS_SYLLABLE is shown in Figure 5.13.

The effect in Figure 5.13 is, of course, quite similar to Figure 5.12. Once again, the two English utterances have strong predictions with more complex syllables and the Spanish utterances have strong predictions with simple syllable types. However, in this case, the behavior of the two Portuguese utterances is observable. In terms of complex syllables, Portuguese 1 and Portuguese 2 group quite tightly with the two Spanish utterances; both languages are unlikely to have extremely long syllables. However, in terms of simple syllables, the two Portuguese utterances behave as an intermediately timed language. Returning to Dasher and Bolinger's (1982) concept that stress-timed languages have simple syllable types, Portuguese appears to have more simple syllable types as compared to English, but more complex syllable types than Spanish (in the area of 1 to 2 letters per syllable, at least). Recall that Portuguese, and especially European Portuguese (the variety represented in the current data) has generally been classified as an intermediately-timed language in terms of rhythm (Frota and Vigário 2001). This analysis appears to reflect just this.

As compared to the previous analyses in the current chapter, indeed in the current dissertation, the analysis of the utterances according to syllable structure appears to reflect traditional rhythmic typology. This is more notable given that this is also the first analysis

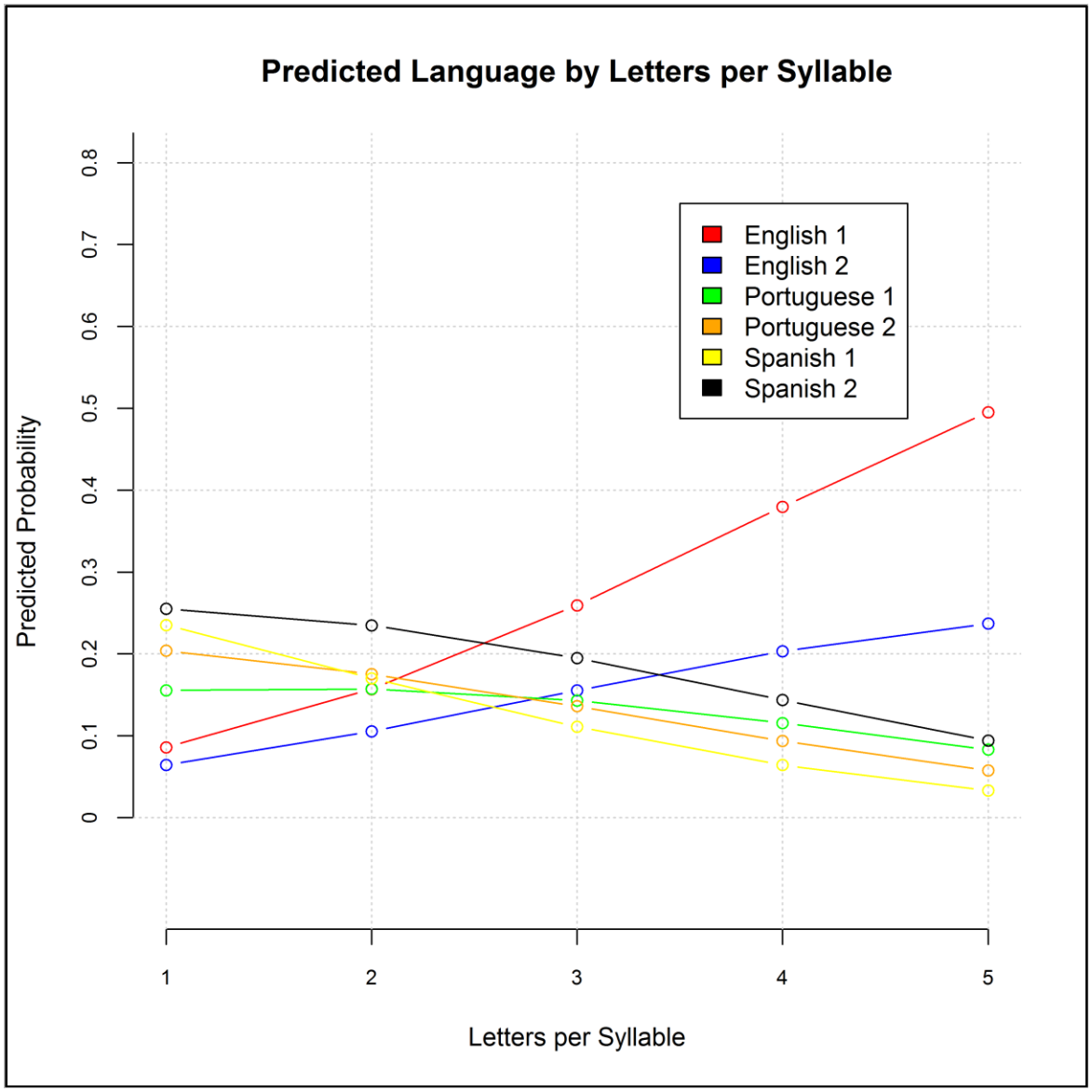

Figure 5.13: The predicted probability of each UTTERANCE according to letters per syllable. In this case, all six original utterances are included, rather than the five used in the current chapter's multinomial analysis, in order to investigate language typology.

identifying these rhythmic differences on the basis of a few phrases, or just a few speakers of these data where the various utterances consistently group according to language. This reflects the general conclusion that speech-rhythm generalizations can be identified by

phonological features of a language, but speaker production is varied enough that is far less reliable.

5.4. Discussion

This chapter (as well as the analysis of **Chapter 4**) provides a unique methodology in speech rhythm research; by combining perception and production data in the same analysis, a new paradigm is presented that avoids assumptions along the lines of traditional rhythm class distinctions. Instead, it defines the relative rhythmic similarity of utterances (via the perception experiment in **Chapter 4**) before undertaking an analysis of the production of these utterances. This production analysis is based upon both traditional and novel metrics for speech rhythm study.

While the results of this chapter are quite promising for speech rhythm research, there are two potential shortcomings of the data analysis that should be mentioned. Firstly, the data set upon which this chapter is based is quite small, being comprised of 6 utterances of approximately 10 seconds each. While a relatively large amount of prosodic cues can be extracted from a data set this small, it does lead to the question of just how representative these particular utterances are of the dialects/ languages that they represent. It is for this reason that the conclusions reached herein are treated as a) representative of individual speaker variation in speech rhythm productions, and b) indicative of those prosodic elements that prompt perceptual differences in speech rhythm (here **Chapter 4** is also important). The only point where language- wide conclusions (or projections, at least) are possible in when discussing the post hoc analysis of syllable structure, where the languages behaved according to traditional rhythmic typology in a very uniform

manner. On the subject of speech rhythm perception, it is also worth mentioning that the limitations of the perception experiment in **Chapter 4**, which was necessary to the analysis of **Chapter 5**, necessitated the small data set used.

The second concern about the current analysis concerns overfitting. Data overfitting occurs when the model (the predictors and interactions intending to predict the dependent variable) is particularly well fit to predicting the dependent variable in the current data, but fails to generalize to other similar data sets. This occurs when the predictors are used to fit the idiosyncratic distribution of the data set, but the predictors cannot be generalized to language in a more general manner, which of course is (often) the goal of linguistic investigation. This is a concern for the current dataset, as the predictors are able to classify the dependent variable in a very accurate manner. The solution to this, which is beyond the scope of the current investigation, but should be considered in future research is to apply the same predictors and interactions identified as significant predictors of UTTERANCE by the multinomial analysis and apply them to a novel data set. If these same predictors are able to classify the dependent variable with an accuracy level that is a significant improvement over chance, this will indicate that the model can be applied to different data sets, and not just the data set from which it was generated. Because a perception experiment would be necessary to achieve this, it would not be a practical undertaking at the present moment, but would certainly be worth consideration in future research.

One particularly promising result of the current chapter is the introduction of a new manner of considering the standard deviation of segment durations. While previous literature has considered the mean standard deviation of segment durations for a phrase or

speaker (e.g. Ramus, Nespor, and Mehler 1999) or the standard deviation of two consecutive segment durations (Harris and Gries 2011), the current chapter instead took the standard deviation of segment across two phonological constituents, the *phonological phrase* and the *intonational phrase*. As mentioned, these constituents were based upon previous literature, specifically Selkirk (1984) and the ToBI system (e.g. Beckman and Ayers Alam 1997). According to the random effects ensemble methodology, the standard deviations calculated across both of the aforementioned constituents outperformed the pairwise standard deviation variables. Furthermore, they are far more informative from a statistical standpoint as compared to the mean standard deviation mentioned. Firstly, modern computational methodology makes a measure of central tendency such as the mean unnecessarily simplistic, as it summarizes a lot of potentially valuable information. Secondly, as was the case with the PVI scores, to the author's knowledge, no previous literature presenting mean standard deviations as a metric of speech rhythm has demonstrated that these standard deviations are normally distributed. Thus, this chapter's new methods for calculating standard deviations of segment durations represents a significant contribution to speech rhythms. In terms of metrics of speech rhythms, this chapter also provides further evidence to the unfit nature of the PVI as a correlate of speech rhythms. Because this has been well discussed in several preceding chapters as well as the current chapter, the shortcomings of the PVI will be mentioned about this at the moment.

The other conclusions of the current chapter that are noteworthy were both mentioned previously. It is clear that speech rhythm in terms of segment duration variability do not behave individually, or 'in a vacuum'. Instead, these cues interact with

other prosodic cues; specifically, the multinomial analysis in the chapter shows that they interact with intensity and pitch. However, given that the variability of pitch was a significant predictor of UTTERANCE in the Random Forest analysis, it is also probable that pitch cannot be ignored in studying the perception of rhythms; this concept is further reinforced by the post hoc analysis, which demonstrates that the standard deviation of pitch in the intonational phrase varies with token frequency. Finally, as mentioned, while some languages do behave in agreement with traditionally defined speech rhythm classes, speaker performance often makes it difficult to empirically verify speech rhythm. This is particularly clear in viewing the post hoc analysis, which shows that, despite major differences in terms of speaker performance, the various utterances group strongly together by language in terms of syllabic structure. This is in agreement with Ramus, Nespor, and Mehler (1999) who conclude that their variables, %V and ΔC reflect rhythm class due to the varying syllabic structure of languages. They associate a greater variety of syllable types with ΔC, as languages with greater complexity of syllabic structures will also show more variability in consonantal interval lengths. In a similar manner, they suggest that those languages with more complex syllable types will have more consonants, thus a lower %V.

This effect closely matches speech rhythm typology. This is the major conclusion of this chapter: while traditional speech rhythm typology is strongly related to the syllabic structure of a language, these structural differences are often not immediately apparent in production data due to the idiosyncratic performances of individual speakers. Thus, one can easily correlate more complex syllable types with so-called stress-timed languages

and more simple syllable types with syllable-timed languages, but these differences are not always apparent in the absence of extremely large data sets.

Chapter 6.

Implications, Directions for Further Study and Concluding Remarks

Overview

This concluding chapter will discuss the linguistic and practical implications of the various studies discussed in this dissertation, as well as suggesting further steps in speech rhythm research given the results of this dissertation. It begins with a summary of the results and discussion of the current research. The implications for linguistics follow, focusing specifically on typological implications. These conclusions are presented in perspective of the current state of phonetics/ phonology in order to provide a more complete perspective of the importance of the findings. The next section reviews the methodological implications of this dissertation and is followed by a discussion of the current research on a practical level and the potential application of these findings to non-academic fields, i.e. technology development and forensics. It then discusses the implications of the current dissertation for future speech rhythm research, considering some shortcomings of the current dissertation, methodological aspects of the various speech rhythms studies and how they may be applied to other linguistic queries, as well as new directions for speech rhythm research. Finally, some concluding remarks are presented.

6.1. Dissertation Summary

This dissertation set out to a) comparatively assess the speech rhythms of two different dialects of Spanish, as well as to compare the rhythms of English, Portuguese, and Spanish; b) assess the efficacy of various interval metrics that have been used to classify and compare speech rhythms in previous literature; and c) develop new IMs for speech rhythm classification and introduce a new paradigm in speech rhythm research.

Chapter 1 reviews past literature on speech rhythms and discusses some methodologies employed in attempts to quantify these rhythms. Specifically, it shows that, according to previous literature, languages (and dialects) do indeed appear to differ in terms of rhythm. However, conclusive empirical proof of the existence and anture of these differences, either from production data or perception data, has not been presented.

Chapter 2 uses the PVI, a widely adopted metric reported to distinguish between languages (and dialects) of different rhythm classes (e.g. Low and Grabe 1995), in an attempt to distinguish between the speech rhythms of monolingual Mexican Spanish and bilingual Chicano Spanish speakers. While this chapter gives some evidence that these two dialects differ in terms of rhythms, with bilingual speakers showing less vowel duration variability, it also identifies shortcomings in the use of the PVI as a metric of vowel duration variability. Specifically, the use of the mean PVI as a measure of central tendency is unsound, as the PVI scores do not appear to be normally distributed. Furthermore, this simplistic methodology removes a large amount of variation in the data, leaving far less informative results, as compared to more sophisticated methods of calculating IMs. Even when the PVI scores are considered as a series of values, with no measure of central tendency, the resulting predictive power of the model is extremely low.

This is all to suggest that the PVI proves largely ineffective in distinguishing between languages on the case of differing speech rhythms.

Chapter 3 reevaluates the same data, but this time employs a multifactorial regression, which allows the simultaneous consideration of a variety of IMs, as well as their potential interactions. Three major conclusions are drawn in this chapter. Firstly, once again, the PVI proves to be a largely ineffective metric in predicting monolingual versus bilingual Spanish. Secondly, other IMs, specifically those related to the standard deviation of vowel durations measured in a pairwise manner prove to be more effective in distinguishing monolingual Mexican and bilingual Chicano Spanish. Thirdly, these measures of vowel duration variability vary with corpus-based word frequency, meaning that speakers use vowel durations differently when a word is more or less frequent.

Chapter 4 is a perception experiment. In this chapter, 6 utterances (2 English, 2 Portuguese, and 2 Spanish) are low-passed filtered in order to preserve only syllabic rhythm. Participants are then asked to rate the relative similarity of these utterances. A cluster analysis indicates that while all the English and all the Spanish utterances are rated as maximally different, the two Portuguese utterances are rated as similar. This is interesting in that Spanish and English are traditionally considered to be maximally different in terms of rhythm, with the former being syllable-timed and the latter being stress-timed. Portuguese, meanwhile, is considered an intermediate language in terms of rhythm (Frota and Vigário 2001), displaying some stress timed characteristics and some syllable-timed characteristics. However, in this chapter it is Portuguese that proves maximally different from Spanish and English, which are classified as similar at times. The results of **Chapter 4** serve as the dependent variable for the following chapter.

Chapter 5 analyzes the acoustic properties of the utterances used in the perception experiment in order to evaluate what, if any, prosodic correlates (e.g. segment duration, pitch, intensity) prompt the perceptual differences identified in **Chapter 4**. It begins with a Random Forest analysis of a several variables in predicting UTTERANCE (*English 1*, *English 2*, *Portuguese*, *Spanish 1*, *Spanish 2*). These variables represent both traditional and novel metrics that could contribute to perceived differences in speech rhythms; they include measures of segment duration variability, pitch variability, and intensity variability. Once the most effective predictors are identified, this chapter uses a multinomial regression in order to identify those variables and interactions that significantly predict the dependent variable. **Chapter 5** concludes that segment duration variability does indeed contribute to our perception of rhythmic difference, but that pitch and intensity do as well. Several *post hoc* analyses follow. Of particular interest is the analysis that shows the complexity of syllabic structure appears to group the various the various utterances by language according to rhythmic typology, with the syllable-timed English having the most complex syllable structures, the stress-timed Spanish having the most simple syllable structure, and the intermediately-timed Portuguese falling between the two. This suggests that perceived differences in speech rhythms may be an artifact of the syllabic complexity of a language, but that variation in speaker performance makes these differences hard to quantify on the basis of a few utterances or a few speakers.

The studies described here not only represent a step forward for empirical speech rhythm research, but also introduce a new research paradigm. **Chapter 3** addresses the importance of the consideration of corpus-based frequency measures in speech rhythm

research[14]. **Chapters 4** and **5** introduce a methodology that allows the consideration of both production and perception data in two linked analyses. This avoids making any assumptions about the rhythm class of the languages represented by the data beforehand. **Chapter 5** also introduces several new metrics for speech rhythm classification and comparison, particularly those based upon prosodic constituents, as well as identifying the importance of pitch and intensity in speech rhythm perception. In this manner, the current dissertation represents a thorough statistical evaluation of traditional speech rhythm metrics, the introduction of a new research paradigm, and the development of several useful metrics for empirical studies of speech rhythms. Furthermore the multinomial analysis and *post hoc* analyses of **Chapter 5** suggest that perhaps speech rhythms should be considered in terms of syllabic structure, as the utterances tested appear to reflect traditional rhythm class distinctions. This would suggest that the next logical step in speech rhythm research is to correlate the results of studies of the production and perception of speech rhythm with corpus-based data that compare the syllabic structures and word frequencies of the languages considered. As mentioned, the results of a *post hoc* analysis of **Chapter 5** do suggest that in terms of syllabic structure, Spanish and English are maximally different, while Portuguese falls between the two, as suggested by traditional rhythmic class distinctions (e.g. that Spanish is syllable-timed, English is stress-timed, and Portuguese has an intermediate rhythm). In this manner, the current dissertation, in addition to being methodologically innovative, is informative as to the relative positions of English, Portuguese, and Spanish on the speech rhythm continuum.

[14] A consideration already laid out by Harris and Gries (2011), who discuss the role of corpus-based frequency data in speech rhythm research.

6.2. Linguistic Implications

This section will discuss the implications of this dissertation for linguistic theory. It will cover implications for the studies of speech rhythms, language typology, and broader ones still for phonetics/ phonology.

As mentioned, in the introduction, the study of speech rhythms is a well-studied area of linguistic investigation. This being said, there is still very little consensus in the study of speech rhythms, and no universally accepted methodologies for their quantification. To this field of study, the current dissertation adds some productive descriptions of the behavior of speech rhythms. One conclusion is mentioned above, namely the concept outlined in **Chapter 5**: perceived differences in speech rhythms (that is, the traditionally described speech rhythm distinctions) appear to be a product of two factors, one of which is an artifact of the particular language being spoken, and one of which varies with speaker production as influenced by a series of factors such as, but not limited to, dialect, register, languages in contact, age of speaker, speaker sex, etc. The factor which is related to the language spoken and can be said to largely reflect traditional rhythm typologies is the relative complexity of the syllabic structure of a language. There is an observable trend suggesting the import of a language's syllabic structure in terms of purported position on the speech rhythm continuum. While this has been suggested in the past (e.g. Dasher and Bolinger 1982), current speech rhythm research seems to have largely ignored the role of syllabic structure in speech rhythm. This is perhaps the most surprising conclusion of this dissertation: that the data reflect traditional rhythmic typologies in terms of syllabic structure. This is to say that the concept that languages are arranged along a rhythm continuum, with certain more extreme languages at the

respective syllable and stress-timed poles, and more intermediate languages falling between the endpoints holds up in light of the post hoc analyses of **Chapter 5**. The reason that this is surprising is because the past 20 to 30 years of speech rhythm research has attempted to find these distinctions. While the metrics and methodologies used to quantify these differences seem to have only crudely suggested these distinctions (for the most part), the current dissertation has shown that the intuition about rhythmic differences appears to be correct (although, the concept that speech rhythms are a dichotomy does not hold true). This is to say that, at least in the case of speech rhythms, tried and true typological assumptions seem worthy of investigation.

The second factor contributing to speech rhythm distinctions is segment duration variability and, to a lesser extent, F0 and intensity. It is precisely segment duration variability that has been the focus of the majority of speech rhythm research over the past twenty years; these studies have been trying to summarize segment duration variability (and, in particular, vowel duration variability) in order to distinguish between languages of different rhythm classes. While factors such as syllable duration variability and vowel duration variability do appear to contribute to our perception of rhythmic differences, due to a great amount of variation in speaker performance, it is hard to summarize rhythmic differences solely on the basis of a few utterances or a few speakers of any given language. It is also noteworthy that other factors, namely F0 and intensity, interact with vowel and syllable durations, making the concept of studying speech rhythms, and especially speech rhythms perception 'in a vacuum', so to speak, hasty. While **Chapter 5** shows that syllable duration variability contributes most to perceived differences in speech rhythms, both pitch variability and intensity variability contribute significantly as

well (see Figure 5.4). Despite the fact that these other prosodic cues may not constitute what we have traditionally termed syllabic rhythm, as they do vary with segmental duration, they cannot be ignored when considered what contributes to perceived rhythmic differences in spoken language.

Consider also that the results of STRESS : UTTERANCE in predicting DURATION_S (that is, the interactions between if a syllable has lexical stress or not in differing utterances predicts the duration of the syllable) indicate that vowel reduction does not behave uniformly in two different utterances in the same language from the same speaker. This is a further indication that small scale production-based rhythm studies will continue to fail to identify rhythmic variation according to language-based rhythm classes. This is not to say that the study of speech rhythms via production-based studies should be completely abandoned. However, given the great amount of variation amongst speakers of the same language that has often rendered such studies less-than-optimal, the addition of a corpus-based study of the syllabic structure of the languages examined would greatly aid in the interpretation of the results of the production-based studies. Additionally, I would like to suggest that another practical solution to this issue would be large data sets of production data that might allow some typological conclusions to be reached. Perhaps in the presence of larger data sets, speaker variation will be overshadowed by larger typological patterns. In practical terms, automated segment boundary marking such as that of Loukina et al. (2009) offer a particularly promising avenue in both eliminating researcher bias and allowing for the collection of large sets of data.

I would also like to make an observation regarding the various IMs used in this dissertation. When addressing segment duration variability, there are 3 different scales of IM: a) those IMs that deal with segment duration variability on a very local level, between just two adjacent syllables, such as the PVI or SD_PAIRWISE (SD_LOG from **Chapter 3**); b) those IMs that deal with segment duration variability on a larger scale, the phonological phrase, such as SDS_PHON_PHRASE and SDV_PHON_PHRASE; and c) those IMs that deal with segment duration variability on the largest scale in the current context, the intonational phrase, such SDS_INT_PHRASE and SDV_INT_PHRASE. It is noteworthy that in terms of efficacy in classifying the utterances in **Chapter 5**, (b) is more effective than (a), and (c) is more effective than (b). Given that the dependent variable of this model was determined according to perception data, it would appear that differences in speech rhythms are determined according to a relatively large segment of an utterance or sentence. Those metrics that focus on a more local segment, comparing the variability of two adjacent syllables, do not prove to be significant in classifying UTTERANCE in the Random Forest analysis (see Figure 5.4). Even those variables that consider a smaller segment of the utterance do not perform as well as those variables that consider the segment duration variability in the larger intonational phrase. This suggests that speech rhythm differences are not perceived only on the level of immediately adjacent syllables, but across a speech signal lasting several seconds. In terms of just how speech rhythms behave, perhaps they serve in helping distinguish prosodic constituents. Past literature has suggested that infants and children exploit speech rhythms in order to parse words and intonational units; for instance, Nazzi, Bertoncini, and Mehler (1998) show that the acquisition of English rhythmic patterns influences how infants segment speech into

word-like constituents and Gerken and McIntosh (1993) show similar results for speech segmentation during early childhood. The data presented in **Chapter 5** suggest that even larger segments of the speech signal appear to be cued by differences in segment duration variability, as evidenced by changes in segment duration variability metrics across different phonological units. Past literature has suggested that prosodic cues contribute to the parsing of phrases; for instance, Leas (1976) advocates the use of pitch in automatically determining phrase boundaries. Thus, the fact that syllable duration variability, pitch variability, and intensity variability appear to vary between intonational phrases is a plausible extension of the concept that one role of prosodic cues is to indicate intonational boundaries to ease the parsing of speech. This is also in agreement with literature that shows that speech timing is not simply an artifact of the time necessary to produce each segment contained in an utterance (e.g. Kozhevnikov and Christovich 1965, Allen 1969, Lehiste 1971, 1972).

In consideration of the literature mentioned in the previous paragraph, one implication that has not been addressed in the current dissertation is worth discussing: how are speech rhythms actually acquired by speakers? As mentioned, it is clear that segment durations (amongst other prosodic cues) are used to mark the boundaries of phonological constituents. However, these higher-level cues seem to be strongly engrained in a speaker. Ohala (1975) showed that there appears to be some underlying pattern or structure to the timing of speech, as opposed to each segment being produced when the previous segment is complete. Additionally, Wretling and Erikson (1998) showed that it is difficult to mimic the timing of phonemes, suggesting that this timing is somehow hardwired into an adult speaker's phonological system. However, as seen in

Chapter 3, the effect of the use of English is visible in the rhythm of Spanish/ English heritage speakers, despite their having acquired what was throughout their infancy and early childhood a monolingual Spanish prosodic system; these speakers were born to monolingual speakers of Spanish. Several studies have shown that the rhythmic system is acquired at a very young age (e.g. Nazzi, Bertoncini, and Mehler 1998), likely the parsing of words or intonational units. The current dissertation suggests that while rhythm does appear to be employed at a young age (as suggested by the aforementioned literature), rhythmic systems are capable of undergoing change in the case of language contact. For this reason, there is still more research required to better understand about the period when prosody, and rhythm in particular, is acquired and how easily this feature can be altered after acquisition.

6.3. Methodological Implications

As there have been several different experimental approaches employed throughout this dissertation, this section will consider three noteworthy methodological aspects of this dissertation. First, it will consider interval measures for speech rhythm comparison, then the combination of perception and production data, and conclude withsome statistical implications of the methodology employed

As mentioned previously, the majority of studies of speech rhythms have relied upon interval metrics (IMs) to attempt to quantify speech rhythm production (i.e. Low and Grabe's (1995) PVI or Ramus, Nespor, and Mehler's (1999) ΔV). However, the various IMs employed have been criticized for only quantifying a small facet of the various features that lead to differences in speech rhythm perception. For instance,

Loukina et al. (2011) conclude that no single rhythm measure (or IM) was successful in discerning between all five languages they evaluated. This dissertation is in agreement with previous literatures' criticisms of various traditional IMs. It has pointed out several shortcomings of the PVI in particular (*see* **Chapters 2, 3, and 5**); namely, this metric relies upon an unreliable measure of central tendency given its distribution and is only able to distinguish between a relatively restricted range of word frequencies (at least in the data from **Chapter 3**). Thus, one of the most commonly employed IMs proves to be ineffective in distinguishing speech rhythms.

The combination of production and perception data from **Chapters 4** and **5** proves a promising avenue, not just for the study of speech rhythms, but also in the applications of this methodology to other areas of linguistic investigation. The advantages of this method in the study of speech rhythms has already been mentioned, namely that no assumptions are made beforehand about rhythm class. Instead, it uses cluster analysis of perception data to empirically determine the similarity and dissimilarity of the data at hand. This, of course, is highly beneficial in making no assumptions about the nature of speech rhythms before statistically analyzing the rhythmic characteristics of this data. Other areas of phonetics and phonology may benefit from a similar approach. For instance, studies contrasting intonational differences between dialects may benefit from addressing whether these differences are perceptually salient. Dialectology in general would potentially benefit from this approach in fact; while many features such as vowel quality and tone contours have been attributed as contributing to dialectal variation, the question as to whether these features actually contribute to a perceivable difference may be worthy of investigation. For instance, the variety of monolingual Spanish represented

in the current dissertation, namely Mexico City Spanish, has been described as displaying vowel reduction in unstressed vowels (Lope Blanch 1972). Thus, it is likely that this variety has greater variability in vowel duration as compared to other varieties of Spanish. However, whether this proposed difference is actually perceivable to untrained listeners is also a valid question, as it allows one to evaluate whether differences in speech rhythms contribute to perceived differences between different varieties of a language.

Chapter 5 is informative about the utility of several IMs for speech rhythm comparison. Figure 5.4, in particular shows the relative importance of several variables in classifying the utterances as *English 1, English 2, Portuguese*, *Spanish 1,* and *Spanish 2*. In the end, it is segment duration variability that contributes the most to perceived differences in speech rhythms (e.g. the standard deviation of syllable and vowel durations), but these perceptual differences are also affected by changes in intensity and pitch. This analysis is also noteworthy in that it presents novel methods of calculating these effects that prove to be more effective than traditional IMs in this data. The particular nature of these novel metrics is discussed thoroughly in **Chapter 5**.

Many of the statistical implications of this dissertation have already been touched upon in the conclusion of several other chapters, as well as briefly in the current chapter. This dissertation uses several different approaches to analyze speech rhythms (linear and multinomial regression, cluster analysis, Random Forests). It is worth noting that the statistical sophistication employed herein provides a fine-grained perspective of the factors at play in our perception of rhythms. In addition to the strength of the statistical modeling of the current dissertation, it is worth mentioning that it addresses model assumptions, particularly those of normality and non-collinearity of variables. This

dissertation represents a thorough statistical analysis utilizing a variety of approaches; in this way, it is a good example of advanced methodology in empirically verified linguistic research. With a larger data set, the use of a mixed model would also be possible; this would likely be the next logical step for speech rhythm research in the vein of this dissertation.

It is important that researchers are prepared to use a variety of different statistical approaches according to the nature of the data at hand. In some cases, multiple attempts to analyze the data may be necessary before the correct analysis is identified. Given the state of the field, which increasingly values statistically sound methodology, a thorough statistical approach will serve as a great benefit to our field, encouraging sound research and requiring that linguists are able to justify their methodology. It is important to note that just because an approach may be considered correct, this does not indicate that it is the best approach (and it is critical to consider and address model assumptions). Hopefully this dissertation has served as an example of some of the potential approaches that are available to linguists and will challenge methodologies employed, especially in the study of speech rhythms, which has been historically plagued by faulty methodology and metrics (the current dissertation does not mean to suggest, however, that there are no previous methodologically sound studies of speech rhythms; in fact, several are very advanced, e.g. Loukina et al. 2009).

In analyzing speech rhythms, certain statistical considerations are of vital importance. In particular, analyses of speech rhythms based upon IMs risk multicollinearity, as the metrics are often derived from one another. Ensemble methods such as Random Forest (discussed in **Chapter 5**) have been shown to deal with collinear

variables (e.g. Immitzer, Atzberger, and Koukal 2012:2683). Other examples of questionable statistical methodology have been present in past speech rhythm research. Simple assumptions of models and metrics have been largely ignored (e.g. the use of the *mean PVI method* without proof of normality of distribution, e.g. Low and Grabe 1995). This is to say that it is imperative to more fully consider the statistical implications of the methodologies employed.

6.4. Practical Applications

6.4.1. Technological Implications

The application of prosody in the development of certain technologies is by no means novel. Specifically, Lea (1973, 1976) has long advocated the import of prosodic cues in speech recognition algorithms. However, Lea has suggested cues apart from those most widely associated with speech rhythms. In particular, Lea (1973) suggests that stressed syllables contain more salient information that can be employed in speech recognition systems as they tend to not be reduced and are pronounced with more volume (as compared to unstressed syllables) and Lea (1976) suggests that intonational curves can be used to automatically determine prosodic units which are helpful in the parsing of information by speech recognition technology.

To these conclusions, the current dissertation would like to add the potential import of speech rhythms in speech recognition. An understanding of the syllabic structure of a language (as touched upon in the *post hoc* analysis of **Chapter 5**) and the syllable reduction that commonly occurs in a language would greatly benefit an algorithm intended to perform speech recognition. That is, those characteristics suggested by Dasher

and Bolinger (1982) as contributing to speech rhythms should be taken into account when developing technology for speech recognition. Furthermore, these characteristics must be understood from an empirical (rather than theoretical) perspective. The methodology employed in the current dissertation is helpful in providing some preliminary conclusions on the nature of speech rhythm variation between utterances, speakers, and languages that are potentially applicable to speech recognition technology.

6.4.2. Forensic Applications

The application of prosodic cues to the forensic sciences may prove to be even more valuable in comparison to the potential use of speech rhythms in speech recognition technology discussed in the previous section. Forensic linguistics, in particular, could greatly benefit from the investigation in the current dissertation. Forensic linguistics can be described as the intersection of legal and/or law enforcement interests with linguistic research. In particular, forensic linguistics performs in four areas of investigation: "(i) identification of author, language, or speaker; (ii) intertextuality, or the relationship between texts; (iii) text-typing or classification of text types such as threats, suicide notes, or predatory chat; and (iv) linguistic profiling to assess the author's dialect, native language, age, gender, and educational level" (Chaski 2013:333). Harris, Gries, and Miglio (2014) argue for the use of prosodic data in forensic linguistics. Of particular interest to the current discussion, they argue that the methodologies used in **Chapter 3** of the current dissertation have great potential in dialect identification, which is a segment of linguistic profiling as defined by Chaski (2013). Determining speech rhythms of various speakers (defined narrowly in this context as the variability of vowel durations) may

allow the identification of speakers' dialects. This methodology is promising in that speakers' vowel duration variability varies with word frequency; as the differences in dialect are more visible in words with low frequencies, this information could be exploited in a task intended to identify bilingual vs. monolingual speakers, for instance. By asking comparing speakers' performance in low-frequency words, dialectal identification would be possible.

In addition to the possible applications mentioned above, which is largely relevant to the research in **Chapter 3**, **Chapter 5** is also promising in terms of language identification. In particular, the Random Forest methodology provides an example of a largely automated method that performs extremely well in distinguishing between various utterances. The fact that the Random Forest method is largely automated is a positive trait for forensic linguistics as it helps minimize researcher bias and provides highly replicable methodology. This is in line with Chaski's (2013) best practices for forensic linguistics. Furthermore, the fact that this analysis was performed in the case of a (mostly) impoverished speech signal is promising, as forensic linguistics may often occur in the case of a speech signal that is not laboratory quality; this ties to the concept of forensically viable data (e.g. Chaski 2013), as it appears that this method would be effective even in the case of data with sub-optimal recording quality.

While it is not within the scope of the current dissertation to provide an exhaustive discussion of how these methodologies are directly applicable to technology and the forensic sciences, suffice to say that the potential practical applications of the methodologies outlined herein do appear promising. In fact, in linguistics in general, such practical applications may prove to be vital to the future of the field, as they provide an

impetus for new scholars and potential sources of funding to encourage future research.

6.5. The Future of Speech Rhythm Research

The current dissertation provides several experiments that suggest the next steps for speech rhythm research. In particular, the combination of production and perception data seem a promising avenue for understanding what exactly prompts differences in perceived speech rhythms. By considering the results of these combined production/perception studies in conjunction with corpus data, providing information about both syllabic structure and type/token frequency, a more complete perspective of speech rhythms from both a language-wide typological standpoint as well as in terms of individual speaker production is possible. It is this distinction between language rhythm class as defined by syllabic structure and variation in speaker performance that is central to our understanding of speech rhythms. In addition, as discussed above, the current dissertation does utilize a range of statistically sound methodologies in approaching the data sets in full consideration of model assumption.

One interesting avenue for future speech rhythm research not addressed in this dissertation is the relationship between speech rhythms and meaning. While the current dissertation has discussed the use of rhythms in dividing utterances into smaller prosodic constituents, it has not addressed just what speakers may intend to convey with changes in rhythm. However, it would be hasty to assume that there is no iconicity in speech rhythms. **Chapter 3** showed that monolingual Spanish speakers were able to employ a greater range of vowel duration variability as compared to speakers with lower aptitude in Spanish. This chapter posited that this was due to speakers' abilities to exploit a full range

of vowel duration variability, perhaps for expressive purposes, as compared to heritage speakers. This would suggest that varying rhythms may play a role in expressing a speaker's intended meaning of a word or phrase. Other prosodic cues, in particular intonation, have been shown to play a role in information structure (e.g. Vallduví 1992), expression of emotion (Devillers 2013), expression of surprise (Abelin 2013), etc. The relationship between rhythm and iconicity has not, to the author's knowledge, been explored, but given that other prosodic factors known to interact with rhythm, have been connected to meaning, this avenue of research certainly seems promising.

While this dissertation does represent a step forward for speech rhythm research, there are a few shortcomings worth of distinction. Two issues, discussed in *Section 5.5* are of particular concern; as they have been quite thoroughly discussed, this section will simply remind the reader of these issues, as they will likely be of concern for future speech rhythm research. The first is the size of the data set considered in **Chapters 4** and **5**. In terms of the distinction of speech rhythms via production data, just a few utterances from a few speakers are often insufficient to accurately distinguish languages with IMs, as utterances' productions on a small scale seem to be largely rhythmically idiosyncratic. That is, a single speaker shows a great amount of variation in their rhythmic production. The conclusions of **Chapter 5** are derived from a small data set. This fact is unavoidable, as the analysis is based upon the perception study carried out in **Chapter 4**. However, despite the sparse data, the analysis still allowed several conclusions.

The second issue discussed in *Section 5.5* is data overfitting. This is the case when the model constructed is particularly well-suited to the idiosyncrasies of the data set, so-well so, in fact, that the model does not necessarily apply to other similar data sets. This is

of concern as the predictions and conclusions derived from the model at hand cannot be said to apply to the community of speakers at large. Given a larger data set (see paragraph above), it would be possible to verify that data overfitting were not an issue in the current analysis, particularly in that of **Chapter** 5; for instance, a larger data set would allow bootstrapping to diagnose data overfitting. Shortcomings notwithstanding, the current dissertation represents a significant progress for empirical speech rhythm research.

6.6. Concluding Remarks

As the preceding section has quite thoroughly outlined, the contributions of the current dissertation and its implications for various facets of linguistics and beyond, as well as suggesting the next logical steps in terms of future speech rhythm research, these concluding remarks will be relatively brief. This dissertation addressed a well-studied and contentious area of linguistics, namely the quantification of speech rhythms. It is the sincere hope of the author that two things have been accomplished through the long process of this research. Firstly, hopefully this work has clarified the nature of speech rhythms. One of the goals of this dissertation was to empirically examine the rhythmic nature of English, Portuguese, and Spanish. This was achieved in the preceding chapters, but it is the hope of the current dissertation that some of these conclusions should be able to be extended to other languages (see discussion of data overfitting above). The second goal that has hopefully been achieved by this dissertation is to challenge linguists' methodologies in their approach to all manner of linguistic query. By providing advanced empirical methodology and combining perception and production data, this dissertation has hopefully served to spark thought and discussion, positively influencing the quality of

research performed in speech rhythms, prosody, phonetics and phonology, and linguistics at large.

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Appendix 1
Calculation of Traditional Speech Rhythm Metrics

Example of calculation of traditional metrics of speech rhythm (or interval metrics) based on two fictitious data sets; *see* **Chapter 1**.

1. Data

Consider two different data sets for *Speaker A* and *Speaker B*

Speaker A:
Utterance 1:
Vowel Duration: 65, 78, 105, 45, 59, 89, 130
Consonant Duration: 32, 45, 66, 23, 18, 40, 50, 22
Utterance 2
Vowel Duration: 90, 77, 46, 102
Consonant Duration: 45, 33, 12, 15, 44, 15

Speaker B:
Utterance 1:
Vowel Duration: 48, 66, 36, 102, 143
Consonant Duration: 15, 41, 44, 22, 26
Utterance 2:
Vowel Duration: 88, 29, 66, 59, 89, 111
Consonant Duration: 25, 23, 12, 14, 36, 29, 21
Utterance 3
Vowel Duration: 56, 88, 94, 96, 75, 113, 120
Consonant Duration: 18, 12, 25, 38, 32

2. PVI

2.1 Calculation of PVI (e.g. Low and Grabe 1995):

$\text{PVI}_{\text{SpeakerA- Utterance1}} = \text{PVI}_1 \frac{|(65-78)|}{(65+78/2)} = .18$, $\text{PVI}_2 \frac{|(78-105)|}{(78+105/2)} = .30$, $\text{PVI}_3 \frac{|(105-45)|}{(105+45/2)} = .80$, $\text{PVI}_4 \frac{|(45-59)|}{(45+59/2)} = .27$, $\text{PVI}_5 \frac{|(59-89)|}{(59+89/2)} = .41$, $\text{PVI}_6 \frac{|(89-130)|}{(89+130/2)} = .37$

$\text{PVI}_{\text{SpeakerA- Utterance2}} = \text{PVI}_1 \frac{|(90-77)|}{(90+77/2)} = .16$, $\text{PVI}_2 \frac{|(77-46)|}{(77+46/2)} = .51$, $\text{PVI}_3 \frac{|(46-102)|}{(46+102/2)} = .76$

$\text{PVI}_{\text{SpeakerB- Utterance1}} = \text{PVI}_1 \frac{|(48-66)|}{(48+66/2)} = .32$, $\text{PVI}_2 \frac{|(66-36)|}{(66+36/2)} = .59$, $\text{PVI}_3 \frac{|(36-102)|}{(36+102/2)} = .96$, $\text{PVI}_4 \frac{|(102-143)|}{(102+143/2)} = .33$

$PVI_{SpeakerB-\ Utterance2} = PVI_1 \frac{|(88-29)|}{(88+29/2)} = 1.01,\ PVI_2 \frac{|(29-66)|}{(29+66/2)} = .78,\ PVI_3 \frac{|(66-59)|}{(66+59/2)} = .11,\ PVI_4 \frac{|(59-89)|}{(59+89/2)} = .41,\ PVI_5 \frac{|(89-111)|}{(89+111/2)} = .22$

$PVI_{SpeakerB-\ Utterance3} = PVI_1 \frac{|(56-88)|}{(56+88/2)} = .44,\ PVI_2 \frac{|(88-94)|}{(88+94/2)} = .07,\ PVI_3 \frac{|(94-96)|}{(4+96/2)} = .02,\ PVI_4 \frac{|(96-75)|}{(96+75/2)} = .25,\ PVI_5 \frac{|(75-113)|}{(75+113/2)} = .40,\ PVI_6 \frac{|(113-120)|}{(113+120/2)} = .06$

2.2. Reporting and interpretation of PVI Scores
Low and Grabe (1995) report the mean PVI for utterances as follows:

Speaker A: Mean $PVI_{Utterance1}$ .39, Mean$PVI_{Utterance2}$ .47
Speaker B: Mean $PVI_{Utterance1}$ .55, Mean$PVI_{Utterance2}$ .51, Mean$PVI_{Utterance3}$ .21

This would mean that Mean$PVI_{Speaker\text{-}Utterance3}$ is associated with less variable vowel durations, or a syllable-timed speech, while is associated Mean$PVI_{Speaker\text{-}Utterance1}$ is associated with more variable vowel durations, or a stress-timed speech. Grabe and Low (2002) report a mean for each speaker as follows:

Mean $PVI_{SpeakerA}$: .42
Mean $PVI_{SpeakerB}$: .40

In this case, Speaker B would be associated with more regularly timed vowel durations, suggesting syllable-timed speech, while Speaker A would be associated with stress timed speech.[15]

3. %V
3.1. Calculation of % V (Ramus, Nespor, and Mehler 1999)

$\%\ V_{SpeakerA-\ Utterance1} = \frac{(65+78+105+45+59+89+130)}{(Sentencelength)} = .66$
$\%\ V_{SpeakerA-\ Utterance2} = \frac{(90+77+46+102)}{(Sentencelength)} = .66$
$\%\ V_{SpeakerB-\ Utterance1} =$
$\%\ V_{SpeakerB-\ Utterance2} =$
$\%\ V_{SpeakerB-\ Utterance3} = \frac{(56+88+94+96+75+113+120)}{(Sentencelength)} = .84$

[15] In some literature, it is not clear if speaker's mean PVI scores are calculated on the basis of each utterance mean PVI score, rather than as above (e.g. Carter 2005).

3.2. Reporting and interpretation of %V
Ramus, Nespor, and Mehler (1999) present the average %V for each speaker as follows.

$\%V_{SpeakerA}$= .66
$\%V_{SpeakerB}$= .68

The authors associate lower %V with stress-timed languages, so Speaker A would be associated with stress-timed speech.

4. ΔV
4.1. Calculation of ΔV (Ramus, Nespor, and Mehler 1999)

$\Delta V_{SpeakerA\text{- }Utterance1} = StandardDeviation(65,78,105,45,59,89,130) = 29$
$\Delta V_{SpeakerA\text{- }Utterance2} = StandardDeviation(90,77,46,102) = 24$
$\Delta V_{SpeakerB\text{- }Utterance1} = StandardDeviation(48,66,36,102,143) = 44$
$\Delta V_{SpeakerB\text{- }Utterance2} = StandardDeviation(8,29,66,59,89,111) = 29$
$\Delta V_{SpeakerB\text{- }Utterance3} = StandardDeviation(56,88,94,96,75,113,120) = 22$

4.2. Reporting and interpretation of ΔV
Ramus, Nespor, and Mehler (1999) report mean ΔV for each speaker, so these data would be reported as:

Mean $\Delta V_{SpeakerA}$ = 26.5
Mean $\Delta V_{SpeakerB}$ = 31.7

Although they use this variable in a rhythm experiment, the authors ultimately conclude that ΔV is not directly related to rhythm class (Ramus, Nespor, and Mehler 1999:8).

5. ΔC
5.1. Calculation of ΔC (Ramus, Nespor, and Mehler 1999)

$\Delta C_{SpeakerA\text{- }Utterance1} = StandardDeviation(32,45,66,23,18,40,50,22) = 16$
$\Delta C_{SpeakerA\text{- }Utterance2} = StandardDeviation(45,33,12,15,44,15) = 15$
$\Delta C_{SpeakerB\text{- }Utterance1} = StandardDeviation(15,41,44,22,26) = 13$
$\Delta C_{SpeakerB\text{- }Utterance2} = StandardDeviation(25,23,12,14,36,29,21) = 8$
$\Delta C_{SpeakerB\text{- }Utterance3} = StandardDeviation(18,12,25,38,32) = 10$

5.2. Reporting and interpretation of ΔC
Ramus, Nespor, and Mehler (1999) report mean ΔC for each speaker, so these data would be reported as:

Mean $\Delta C_{SpeakerA}$ = 15.5
Mean $\Delta C_{SpeakerB}$ = 10.4

They associate higher ΔC with stress-timed languages, so Speaker A would be associated with more stress-timed speech while Speaker B would be considered to display syllable-timed speech.

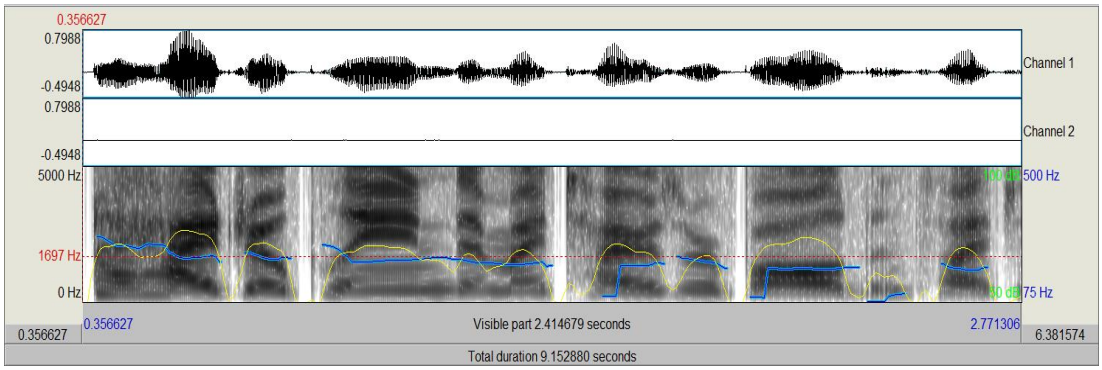
Appendix 2
Perception Experiment Data

Unaltered data from perception experiment and accompanying division of prosodic constituents. See **Chapter 4**.

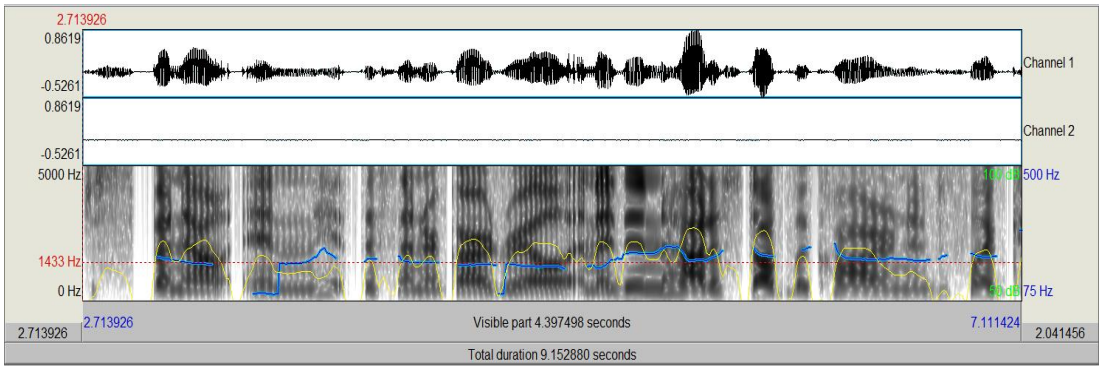
Key:

- IP*X* {}- *Intonational Phrase*, essentially equivalent to level 4 of ToBI
- PP*X* []- *Phonological Phrase*, essentially equivalent to level 3 of ToBI, comprised of a minimum of two prosodic words, may contain multiple pitch accents

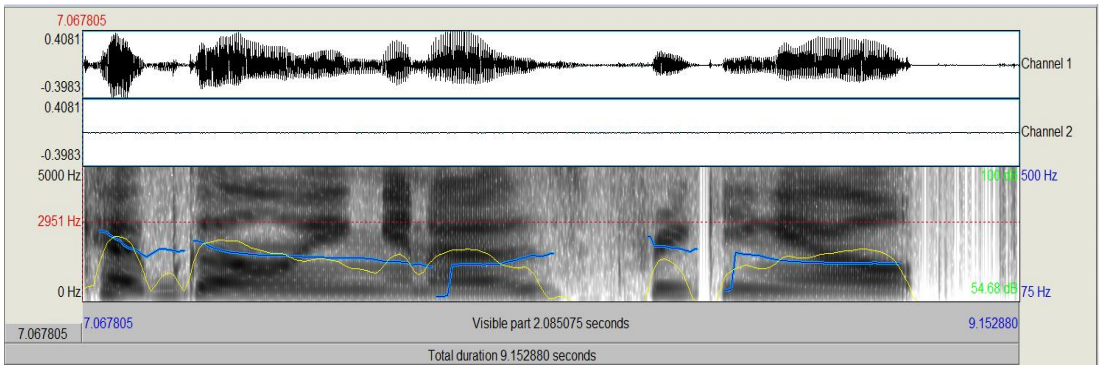
English 1:
I hydroplaned and my tires were bald and so I just spun out and hit the center guardrail and I didn't know how to stop the car and it just like kept going and I was freaking out



IP1{PP1[aɪ ˈhaɪ drəʊ pleɪnd].PP2[ænd maɪ ˈtaɪ.ɜrz wɜr bɔld].PP3[ænd soʊ aɪ ʤʌst]}

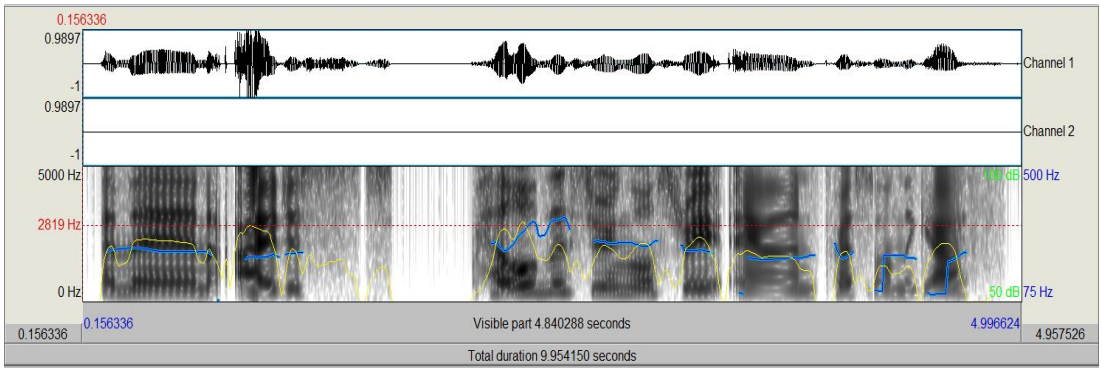


IP2{PP4[spʌn aʊt ænd].PP5[hɪt ðə ˈsɛntər ˈgɑrdreɪl ænd aɪ ˈdɪdənt noʊ haʊ tu stɑp ðə kɑrænd ɪt ʤʌst laɪk]

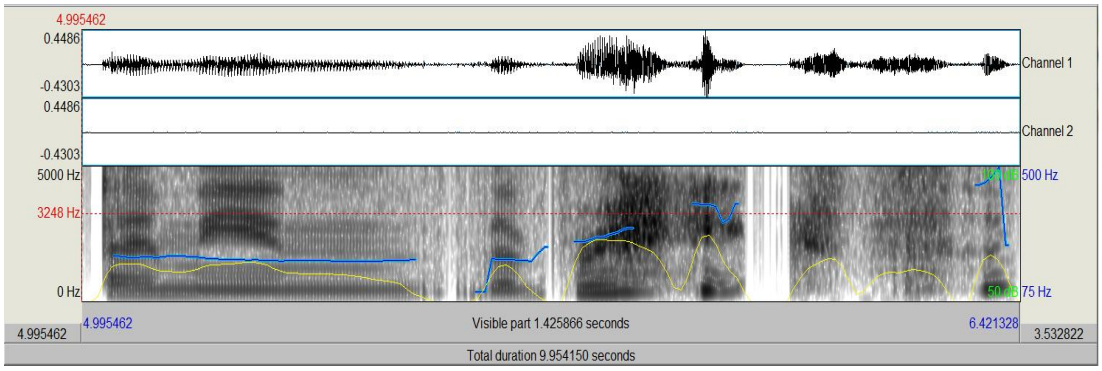


IP3{PP6[kɛpt ˈgoʊɪŋ ænd aɪ wʌz ˈfrikɪŋ aʊt]}

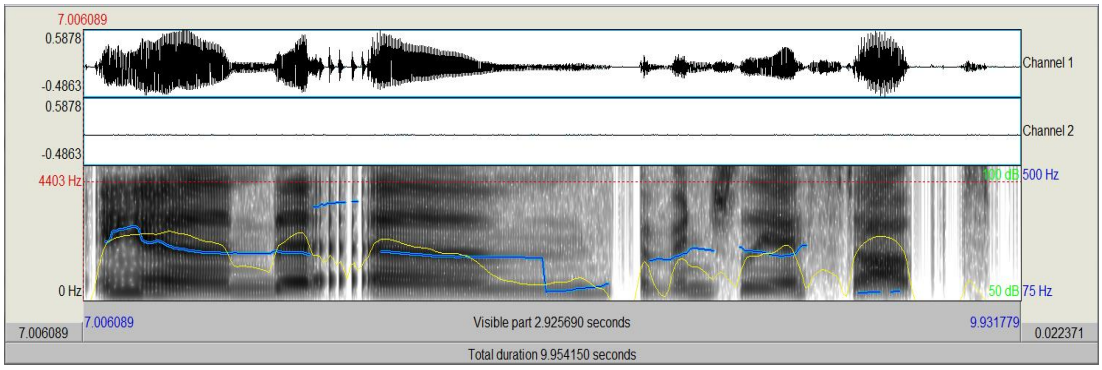
English 2:
And then I just held the steering wheel straight and pressed on the gas, I mean the breaks [laughs], and ummm eventually I stopped



IP1{PP1[ænd ðɛn aɪ ʤʌst].PP2[hɛld ðə ˈstɪrɪŋ wil streɪt ænd].PP3[prɛst ɑn ðəgæs]}



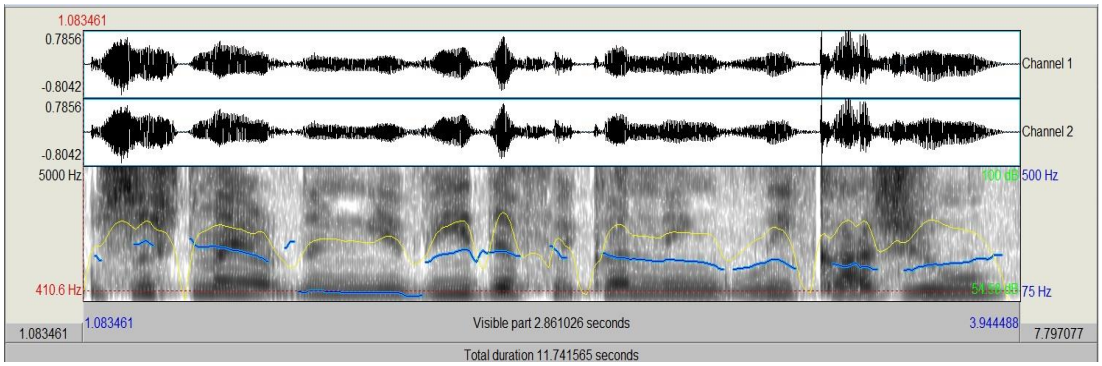
IP2{PP4[aɪ min ðə breɪks]}



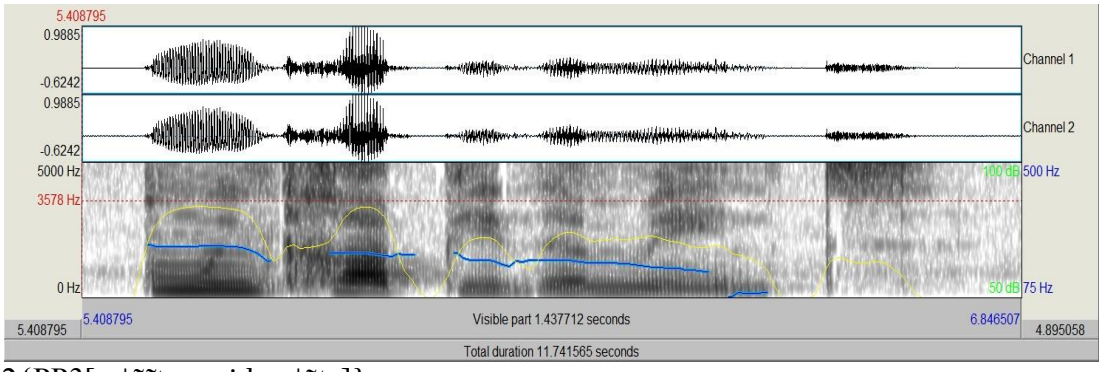
IP3{PP5[ænd ummm].PP6[ɪˈvɛnʧəwəli aɪ stɑpt]}

Portuguese 1:

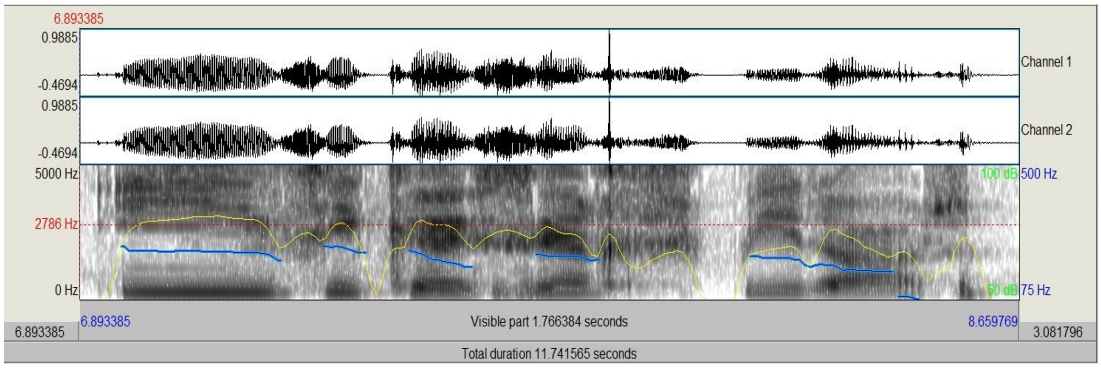
O susto maior da minha vida foi quando engoli caju muito rapidamente e fiquei sem respirar por algum tempo



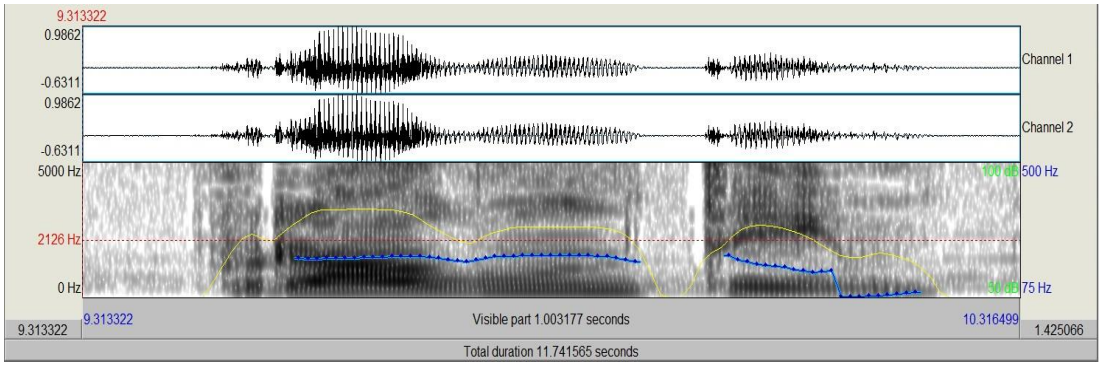
IP1{PP1[u sˈuʃt mɐjˈɔɾ dɐ mˈiɲɐ vˈidɐ].PP2[foj kuˈẽdu ẽgulˈi kɐʒˈu]}



IP2{PP3[mˈũĩt ʁˌapidɐmˈẽtə]}

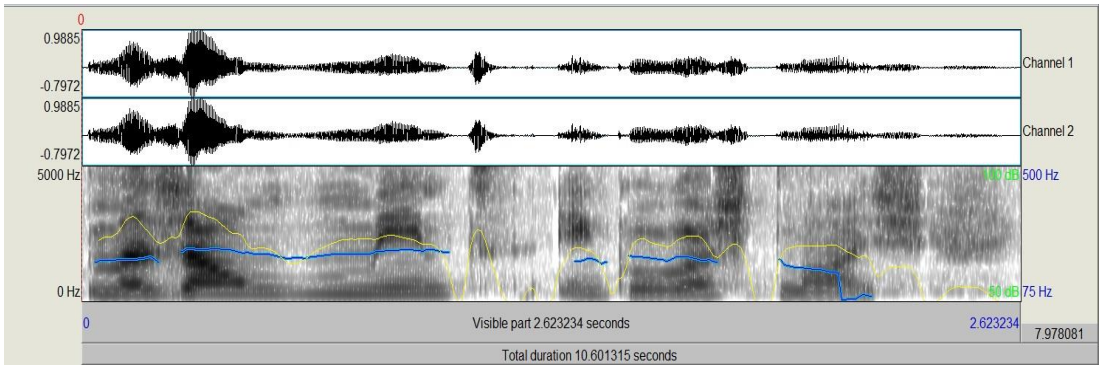


IP3{PP4[ii fikˈɐj sɐ̃j̃ ʁəʃpiɾˈaɾ]

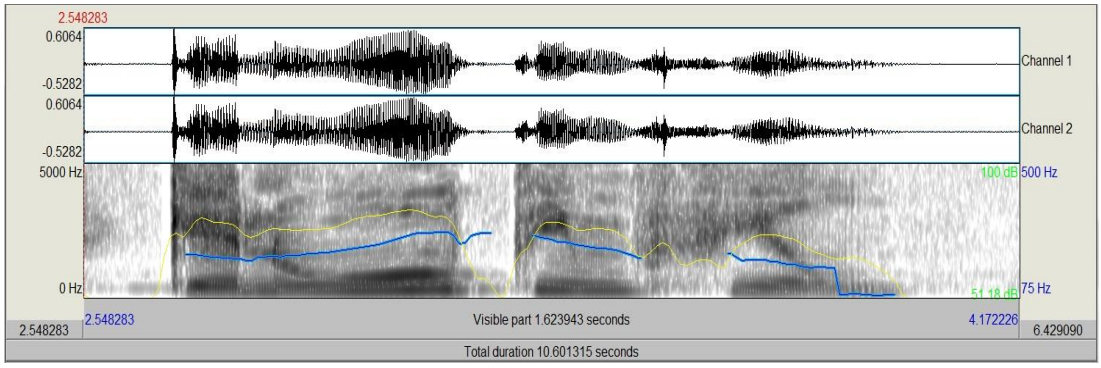


IP4{PP5[puɾ algˈũ tˈɐ̃pu]}

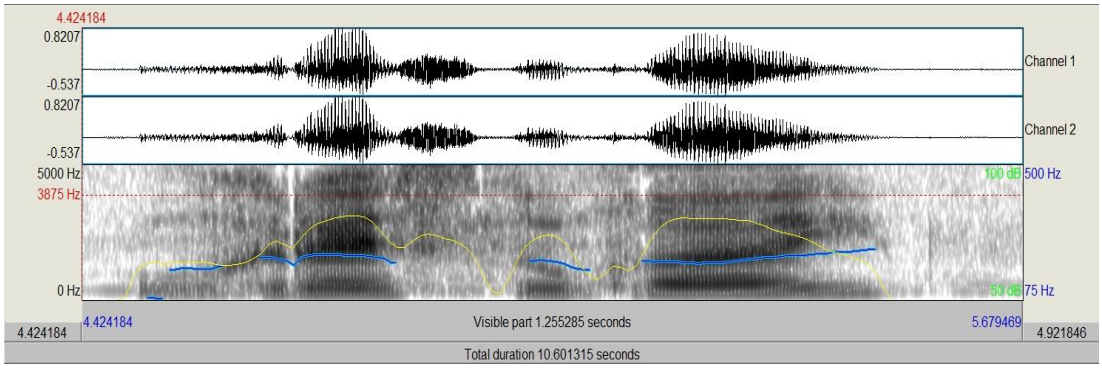
Portuguese 2:
Mas a mente em que gosto mais que no ultimo filme o regresso do rei a batalha final entre os orcs e os humanos



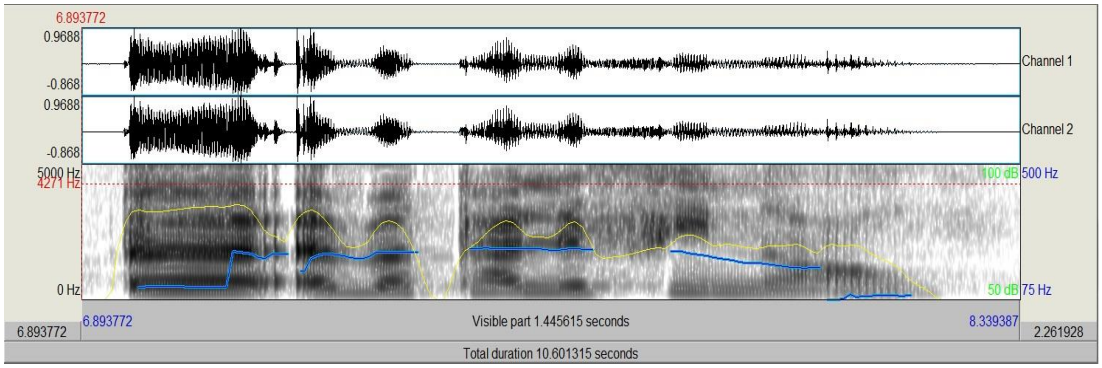
IP1{PP1[mɐʃˈɐ mˈɐ̃t].PP2[ɐ̃j̃ ke kə gˈoʃtu majʃ]}



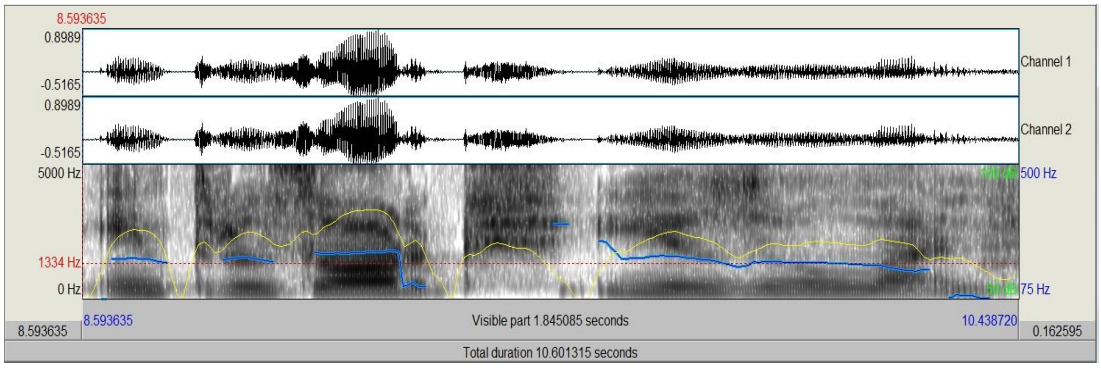
IP2{PP3[kə nu ultˈimu fˈilm]}



IP3{PP4[u ʁəgrˈɛsu du ʁˈɐj]}

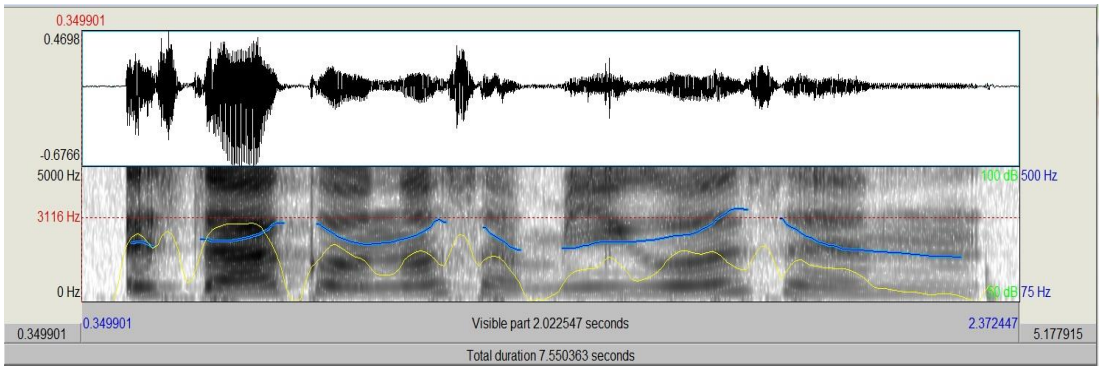


IP4{PP5[ɐ bɐtˈaʃɐ finˈal}

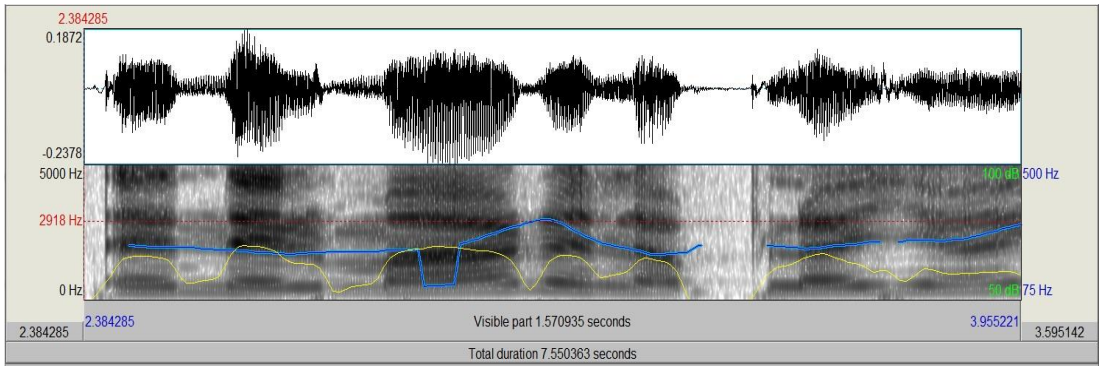


IP5{PP6[ˈẽtrə uʃ ɔrkʃ i].PP7[uʃ umˈɐnuʃ]}

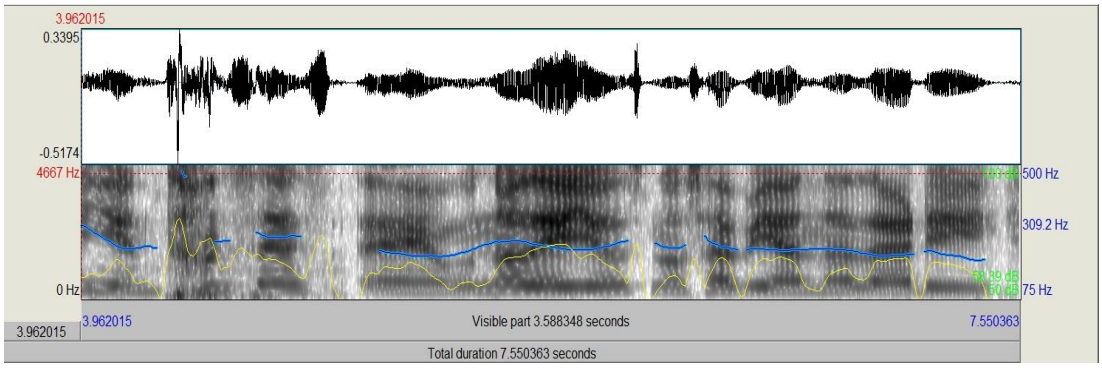
Spanish 1:
Esta(b)a con (u)nos amigos en, en el mar en la playa, y entonces uno de ellos no sabía nadar y.



IP1{PP1[est´aa kon nos a´miɣos en]



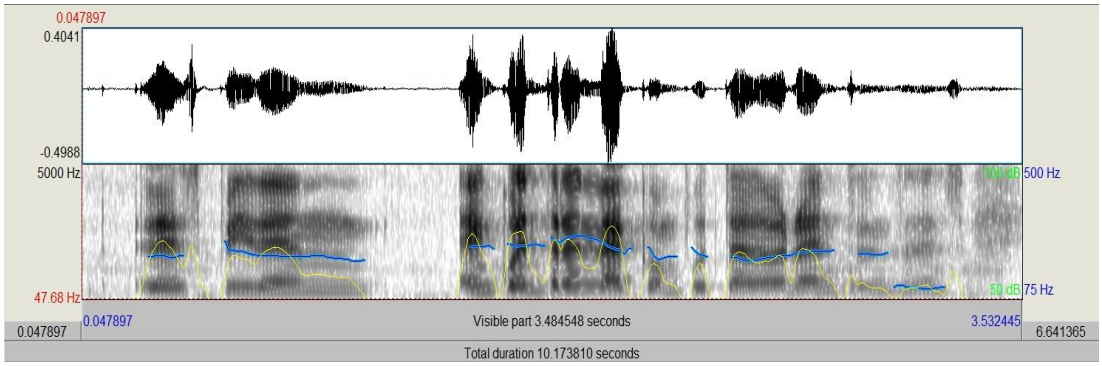
IP2{PP2[en el maɾ].PP3[en la ´plaja]}



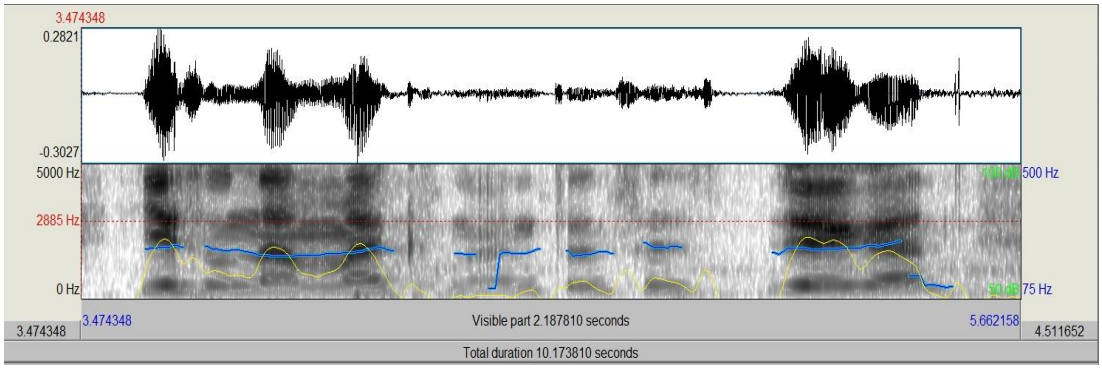
IP3{PP4[i en´tonses].PP5[´uno ðe ´eʌoz no sa´βia na´ðaɾ i]}

Spanish 2:

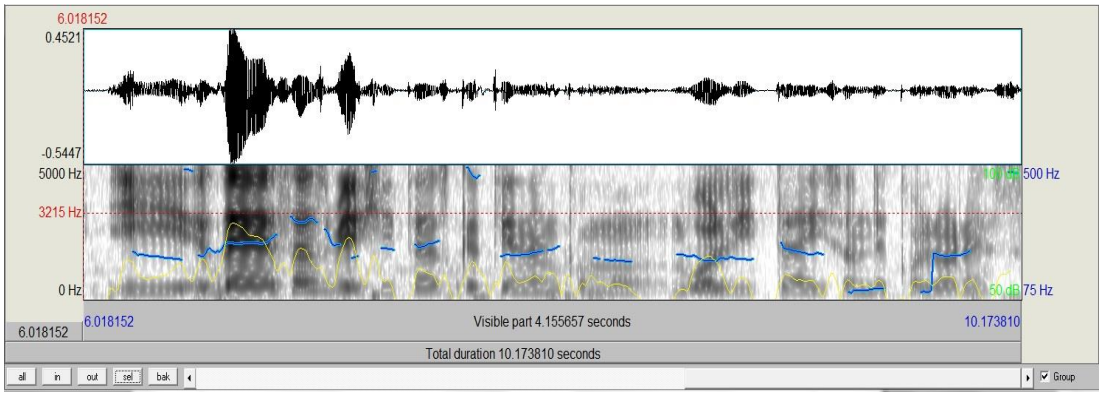
Les piden encuentran la computadora entonces y es una Mac no entonces, llegan, y de esas viejitas que tienen como bolita y son de colores



IP1{PP1[les ´piðen].PP2[eŋ´kwentɾan la komputa´ðoɾa en´tonses]}



IP2{PP3[i es ´una mak no en´tonses].PP4[´ʌeɣan]}



IP3{PP5[i ðe ´esaz βje´xitas].PP6[ke ´tjenen ´komo].PP7[βo´lita].PP8[i son de ko´lores]}