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Multi-frequency segmentation of movement trajectories

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Abstract

This paper presents a new multi-frequency segmentation method for movement trajectories. The method is presented using a case study of a Turkey Vulture data set. The approach shows promising results to automatically extract behavioral modes from movement trajectories at multiple temporal frequencies.

1. Introduction

Computational Movement Analysis focuses on the characterization of the trajectory of individuals across space and time. The end goal is often to understand the behavioral state of the animal by analyzing this complex signal. A level of complexity that is often ignored is the fact that different behaviors occur at different spatial and temporal scales (Ahearn et al. 2001; Ahearn and Smith, 2006; de Weerd et al. 2015; Soleymani et al., 2014). This research proposes a multi-frequency analysis technique that decomposes a movement parameter (i.e. speed) time series, derived from movement trajectories, into a range of spatiotemporal frequencies and then recombines them into the *Multi-frequency Laplacian Series (MFLS)*.

2. Methods

Long-term GPS data of a Turkey Vulture obtained from the Movebank Data Repository was used for our analysis. The data set includes 32,000 fixes with a temporal resolution of 1 hour, tracked over 3.5 years. The data was manually classified by domain experts into four different behavior modes: *breeding grounds*, *fall migration*, *non-breeding grounds*, and *spring migration* (Dodge et al. 2014). This resulted in 18 distinct segments. For this analysis, the trajectory was converted to a *time series* of the speed at each GPS fix as calculated from two sequential fixes.

The approach used to create the multi-frequency decomposition of a trajectory is after Burt (1983). The method generates a new data series, from the original time series, that is effectively, what would result from the convolution of two different sized Gaussian filters (DoG). To generate the series, a number of steps are necessary. First, a Gaussian shaped filter

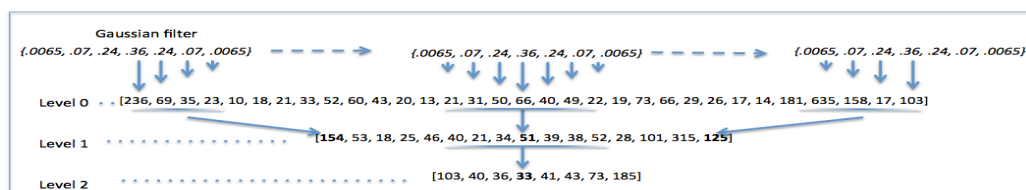


Figure 1: Gaussian Pyramid

is convolved with the series by centering it at every other value in the series (Figure 1, Level 0). The result of each convolution is the next value in Level $x+1$. Recursively applying the method

results in n levels; with each level being $\frac{1}{2}$ the size of the previous Level x . Figure 1 shows 3 levels of the Gaussian series (original plus 2 levels) created using this approach.

The next step is to expand each of the levels of the Gaussian series, obtained from the previous step, to the original size of the series at Level 0, with the same kernel used for reduction. This process is also carried out with a recursive algorithm. Figure 2a is an example of 6 expansion levels plus the original (Level 0, in red), starting with expansion level 6 and going to expansion level 11 (shown in blue).

The third step is to produce the Difference of Gaussian Filters (DoG). This is accomplished by subtracting each expanded level from the previous level (i.e. expanded Level 1 – Level 0, Level 2 – Level 1, ... Level n – Level ($n-1$)). This results in the Laplacian series (i.e. DoG) shown in green in Figure 2a. Where the Laplacian series (a second derivative function) crosses zero, it represents an inflection point called a *zero-crossing*.

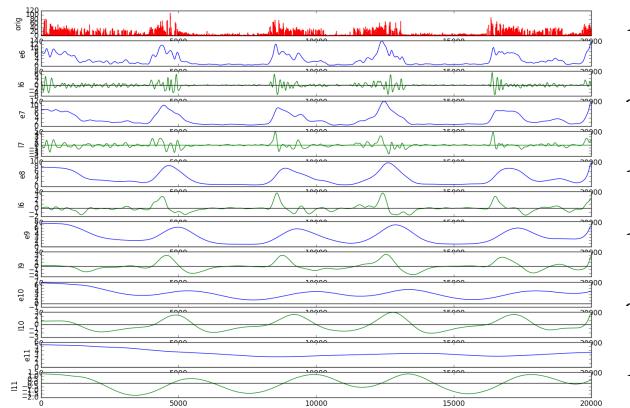


Figure 2a: Original data (red), five level expanded series (i.e. Exp 6-11, in blue) and Laplacian series (Lap 6-11, in green).

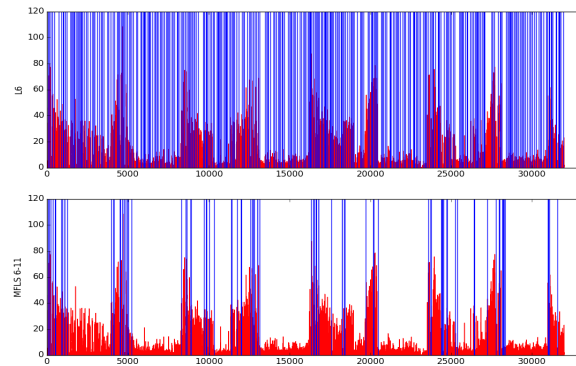


Figure 2b: Laplacian series 6 (top) and Multifrequency Laplacian series 6-11 (bottom) overlaid on original time series.

How to combine this range of frequencies into the *Multi-frequency Laplacian Series (MFLS)* is after Ahearn (1988). The methodology uses a procedure that captures broader scale trends using the lower spatial frequencies, while preserving the higher frequencies that define the beginning and ending of these trends (or behaviors). Combining the levels is accomplished by taking the maximum of the absolute value of the Laplacian value among the different levels being combined (Ahearn, 1988). An additional step taken in this research is to use the penultimate frequency band in the Laplacian series to define the number and approximate location of the transition points (i.e. zero-crossing indexes) between behaviors, and the indexes derived from the MFLS to refine the locations of the transition points. That is, the algorithm finds the closest index in the MFLS to each of the indexes in Level ($max-1$), where max is 11 in this case, and “substitutes” it in its place to create what we call the *MFLS nearest*. Level ($max-1$) was chosen because the analysis showed that one level less than the maximum level often corresponds to the temporal frequency of the longest temporal feature, in this case the seasonal behavioral patterns of the turkey vulture.

3. Results

Creation of the MFLS requires the selection of the starting level in the frequency range to be used in the process. Selection of the ending level (i.e. the lowest frequency band) is done automatically at the level (in this case Level 11) where the model reaches a minimum number of zero-crossings and remains unchanged with the addition of the next level. For the dataset used in this study, Level 6 (L6) is selected for the beginning frequency band. Once determined, the algorithm combines levels 6 through 11 of the Laplacian series.

Figure 2b above, shows a comparison of segments extracted at the zero-crossings (represented as vertical lines) for level 6 (L6 on top) and MFLS6-11 (bottom). Note the lack of definition of the segments related to the seasonal behavior (e.g. migration) of the Turkey Vulture in L6 (top of figure 2b) and the clear definition of separate segments in the MFLS 6-11 (bottom of figure 2b).

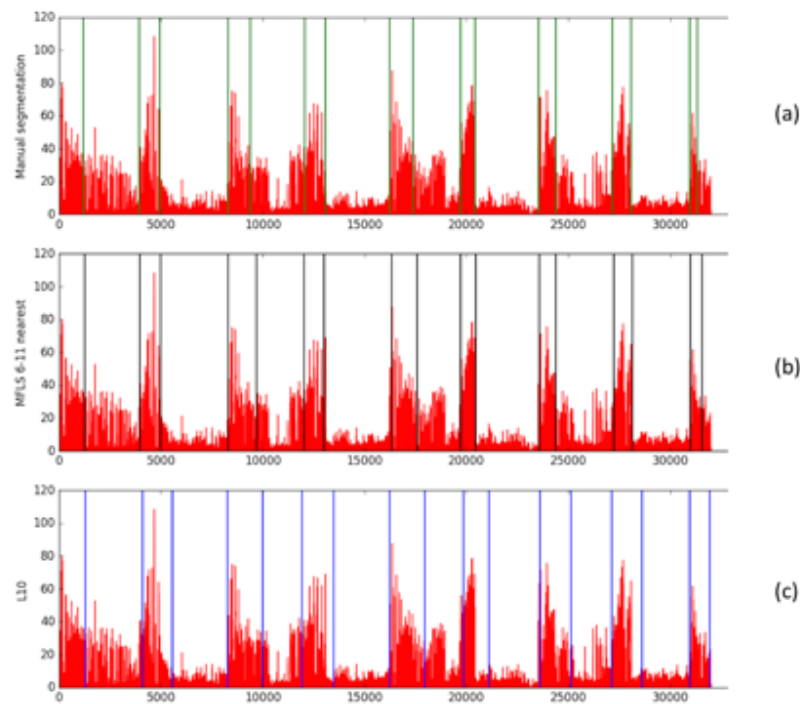


Figure 3: Manual segmentation (a); MFLS 6-11 nearest (b); L10 (c).

Comparison of the results with the analysis conducted by Dodge et al. (2014) was done to get a better understanding of the relationship between the multi-frequency segmentation and a biologic interpretation of the trajectory (Figure 3). In order to do this, the manually segmented trajectory (Figure 3a) is compared with the *MFLS 6-11 nearest* (Figure 3b) and Level L10 of the Laplacian Pyramid (Figure 3c). The manual classification by domain experts resulted in four different behavior modes: *breeding grounds*, *fall migration*, *non-breeding grounds*, and *spring migration* (Dodge et al. 2014) and 18 distinct segments. The L10 frequency band found the same number of segments, 18 as the manual classification. The *MFLS6-11 nearest*, which uses the global scale frequencies (i.e. L10) for defining segments therefor had 18 segments. The difference was

in the timing of the transitions between behavioral modes. The average difference between the transition times of the manual classification and the *MFLS6-11 nearest* was 76 hours. The average difference between the transition times of the manual classification and Level L10 was 326 hours. Given that the time series occurs over a 3.5-year period the precision of the definition of the temporal transition points is quite high (i.e. within 3 days) for the *MFLS6-11 nearest*. It is less so for the L10 due to the smoothing that occurs at this low frequency.

4. Conclusion

The results of this analysis show promise for analyzing a time series at multiple temporal scales. The strength of this methodology is that it captures the low frequency phenomena, in this case the different behavioral modes of the Turkey Vulture, while preserving the high frequency transitions from one behavior to the other. Using just a single frequency level for segmentation will not yield segments that are closely aligned (temporally) with the manually defined segments, thus the need for the MFLS. Additionally, with the exception of the selection of the first high frequency band in the MFLS, the process is totally automated and requires no training, parameterization or thresh-holding.

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