Understanding Human Social Kinematics Using Virtual Agents

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Abstract

A pressing issue in both psychology and agent-modeling communities is the inability to account for the wide variance in human variability and individual differences. Added to this is the further complexity of changing goals and social meaning in a dynamic, sequential interaction. While prior work on artificial agent design has prominently addressed physical cues and nonverbal behavior, there is a lack of emphasis on (1) examining cues in combination, and (2) assessing judgments of social situational meaning. In the current work, we present an ontology of physical behavior (*Social Kinematics*) that accounts for the combinatorial effects of multiple cues, as well as the changing social meaning associated with these different combinations of cues. Here, we assess individuals social situational judgments of multiple combinations of ambiguously-defined virtual agent animations. Ultimately, this paper provides a potentially useful framework that has relevance for researchers in social robotics, agent modeling, and cognitive science.

Keywords: Nonverbal behavior; Social perception; Virtual agents; Situations; Motivation systems.

Introduction

As humans, we are constantly evaluating and re-evaluating social information about others. Is this a friend or foe? Attraction or threat? A subtle glance, a stiffening posture, a quickening gait - Each are basic human physical actions that progressively bring clarity to perceptions of individuals' emotional states and intentions.

How then, do humans generate and distinguish between the social meanings attached to different physical movements? For instance, under which parameters does a particular proxemic distance shift in social meaning from friendly to threatening? How might we systematically define and measure these parameters in isolation, as well as in combination?

To address these questions, we take the following steps: (1) First, we present 4 primary categories of physical movement cues: distance, direction, speed, and gaze. (2) Next, we use animated virtual agents to simulate these 4 categories. A critical point here is that we attempt to offer a "sterilized" contextual framework in the presentation of the virtual agents. That is, a completely ambiguous and undefined context: We provide no social context or narrative description, we present the virtual agents upon a "neutral" blank/white backdrop, and we present the virtual agents' facial expressions as neutral and blank. (3) Finally, we assess individuals' evaluations of these animated combinations of physical cues.

Related Work

The current work builds on existing work using virtual agents to systematically examine human physical movement, while addressing two gaps in the literature, namely the (1) accounting of cues in combination, and (2) the mapping of cues to situational social meaning. Before elaborating on these two points however (See "Virtual Agents"), we first provide a review of prior work on *physical cues* and *situational social meaning* in the study of human behavior.

Human Behavior

Physical Cues Interest in social perception of movement has its roots in work using animated movements of abstract shapes (e.g., triangles, squares) conducted by Heider and Simmel (1944). That work involved understanding if and when humans respond to inanimate entities (e.g., robots, and intelligent agents) as if they have intentions and goals.

Locomotive movement The Heider-Simmel simulation is impacted by features of locomotive movement, such as changes in speed and trajectory, which correlate with greater perceptions on animacy, and distance and degree of movements, which correlate with intention (Roux et al., 2013). Moreover, features such as position, velocity, and acceleration of geometric shapes predict event (narrative) segmentation (Zacks, 2004). Further, walking behavior depictions of human "biological motion" (Johansson, 1973) is considered an intentional (Baron-Cohen et al., 1995; Carey, 1999), goal-directed movement (Dittrich, 1993). As such, we conceptualize distance (position), direction (trajectory), and speed as mechanical features of social kinematics.

Nonverbal Behavior Additional categories of physical movement include the nonverbal behavior cues of proxemics, gesture, and gaze. Proxemics, or social distance, (Hall, 1966), has figured prominently in designing virtual humans (Bailenson et al., 2001, 2003) , and social robots (Mumm & Mutlu, 2011; Walters et al., 2009). Gesture and gaze are unique nonverbal behaviors in that they involve more refined cues than the locomotion or position of the body. While the function and utility of certain gestures (emblems that are symbolic) are largely culturally-specific and socially learned (illustrators that augment speech), other gestures serve more basic, implicit self-needs and emotions (adaptors) (Ekman & Friesen, 1972). Although Gaze is not necessarily a movement per se, it is indeed a nonverbal cue that has its roots in intention and Theory of Mind (Premack & Woodruff, 1978; Baron-Cohen et al., 1995). Moreover, the design and impact of gaze in virtual humans has been well-documented (Lee et al., 2007; Gratch et al., 2002).

Movement Models One prominent framework for codifying human movement is the Laban Movement Analysis (LMA), which has previously been applied in generating gesture animations for virtual agents (Chi et al., 2000; Cassell et al., 2001; Gratch et al., 2002) and robots (Nakata et al., 1998). LMA is composed of four components (Zhao & Badler, 2001): Body, Effort, Shape, and Space, where Body, Shape, and Space define what motion is performed, while Effort describes how a motion is performed. Specifically, Body specifies body parts and the sequencing of a motion, Space describes the location and paths of a motion, and Shape describes the body's changing forms. Of these LMA components, Shape and Effort are most relevant to the current paper.

Another prominent taxonomy of body movement is that of Wallbott (1998), which includes detailed specifications about the upper body, shoulders, head orientation, arms movement, and hand shapes (i.e., fists, pointing). Wallbott's categorization has high explanatory power and specificity in terms of individual body components particularly in terms of describing arm and hand movements. This categorization, however, does not account for locomotive movement.

According to both the Labanian and Wallbott models, gesture is a cue that entails a completely distinct set of specifications. That is, we would have to account for a complete ranges and shapes of arm and hand movements. For instance, the body-specific features of Distance, Direction, and Speed directly map onto mechanical arm-specific features of Position, Direction, and Speed (of arm movements), respectively. As such, we will not address Gesture as a variable in the current work, instead engaging in more comprehensive analysis of Gesture in our forthcoming work.

Social Situational Meaning Pervin (1978) suggested situations retained a narrative structure consisting of: *who* is involved, *where* is the action occurring, and *what* activities are involved. Adapted from the above, Read and Miller (1998) used a model of neural network-based constraint satisfaction processes to organize knowledge structures into a coherent narrative-based structure that include components about *who* (or *what*) did *what* to *whom* (or *what*) under *what* circumstance, *why*, *where*, *how*, *with* what effect (e.g., emotional outcome) (Read & Miller, 1998). While various cues (facial expressions, speech, etc.) are in play in this meaning-construction process, we focus strictly on physical movements and nonverbal behavior of the body.

Rauthmann et al. (2014) recently introduced the DIAMONDS, a taxonomy-based behavioral assessment of personality characteristics, situations, and behaviors. The DIAMONDS consist of situational categories that correspond to its acronym: *Duty* (e.g. work, tasks), *Intellect* (e.g., aesthetic, profound), *Adversity* (e.g., threat, criticism), *Mating* (e.g. romance, sexuality), *pOsitivity* (e.g., pleasant, nice), *Negativity* (e.g., unpleasant, bad), *Deception* (e.g., deceit, lies), and/or *Sociality* (e.g., interaction).

Motivation Systems Read et al. (2017) argue for a conceptualization of situations in terms of motivation-based systems, such as the approach-avoidance system (Elliot & Covington, 2001). That is, all situations may be reduced to two motivations: Do I engage, or disengage? Indeed, the DIAMONDS may diverge according to positive and negative judgments (Rauthmann et al., 2014), which align with approach and avoidance characteristics, respectively (Lewin, 1936; Osgood et al., 1957).

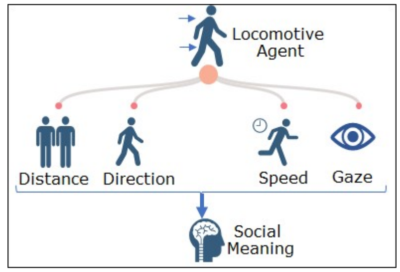

Figure 1: Social Kinematics Model

Virtual Agents

As mentioned earlier, the current study addresses two gaps in the literature using virtual agents to study physical cues: (1) Accounting for the *combinatorial effects* of multiple simultaneous cues, and (2) A structured system of mapping movement parameters onto the perception of *situational social meaning*, which is critical to understanding human behavior (Nisbett & Ross, 1991; Wagerman & Funder, 2009).

Physical Cues While prior work using artificial agents have indeed examined the social impact of physical cues, these are limited in that they often examine cues and situations, in isolation. For instance, many have addressed the impact of proxemic distance using social robots (Breazeal et al., 2009; Mumm & Mutlu, 2011; Hüttenrauch et al., 2006; Walters et al., 2009) and virtual humans (Bailenson et al., 2001, 2003). Recently, however, there has greater focus on the explicit integration of multisensory information in a social context (Zaki, 2013). Further building on this framework, recent work on HRI emphasizes the importance of congruency between cues (Kennedy et al., 2017). Our approach attempts to add to this prior work by presenting a step towards accounting for the combinatorial effects of multiple simultaneous cues. We emphasize that this is the first of a series of planned studies, and although we lay out a comprehensive theoretical model of Social Kinematics and situational meaning, we acknowledge that the analysis in the current paper is by no means comprehensive.

Situational Meaning Prior work has made comprehensive applications of movement categorization into gesture representation in artificial agents (Chi et al., 2000), and examined the impact of categorizations of different body features on emotions (Wallbott, 1998) and personality characteristics (Neff et al., 2010). A gap exists however, in a structured system of mapping movement parameters onto the perception of situational social meaning, which along with personality, represent critical components to understanding and measuring human behavior (Nisbett & Ross, 1991; Wagerman & Funder, 2009). Our approach attempts to adds to these prior work by using an established social situations measurement instrument to assess individuals' judgments of different combinations of physical cues.

Social Kinematics

Building specifically on the body of literature in developmental psychology (i.e., Heider-Simmel), nonverbal behavior, and drawing inspiration from the Laban Movement Analysis and Walbott's Categorization of Movement, we present a typology of movement that 1) distinguishes between body-specific movement (locomotion) and arm-specific movement (gesture), 2) distinguishes between movements performed while standing and while walking, and 3) focuses specifically on contextually meaningful movement. That is, we focus on movements with a social component, as opposed to mere functional movements.

We define Social Kinematics as the socially meaningful features of physical, body-specific movement generated by a social agent (human or non-human) in relation to one or more other social agents. We conceptualize Social Kinematics into features that characterize either body-specific movement (proxemics, locomotion) or gaze. Taken together, we include the following 4 categories in our typology of Social Kinematics, each including 2 levels of features: *Distance* (near, far), *Direction* (towards, away), *Speed* (slow, fast), and *Gaze* (direct, averted). Specifically, Speed corresponds to the LMA component of Effort, and Distance and Direction correspond to the LMA component of Space and Shape, respectively. Levels (Figure 1) of each Social Kinematic Feature (i.e., Towards-Away Directional movement) are similar to the LMA sub-components of Shape and Effort.

Method[1]

Participants

197 participants (145 female, 52 male) were recruited from a undergraduate subject pool at a university in the United States in exchange for course credit.

Experimental Design

The statistical design of this study was a 2x2x2x2 (Distance, Direction, Speed, Gaze) 4-way repeated measures MANOVA to examine the effect of different combinations of movement each at 2 levels (Far-Near, Towards-Away, Gaze-No Gaze, Slow-Fast) on ratings of the 8 situational DIAMONDS (Duty, Intellect, Adversity, Mating (Romance), pOsitivity, Negativity, Deception, Sociality).

Statistical Approach In addition to main effects of individual Social Kinematics, we also examine the 2-way, 3-way, and 4-way interaction effects of each feature. Effect sizes in the present work are reported as partial eta-squared. Though the general rules of thumb for ANOVAs is to measure effect size with eta-squared (Miles & Shevlin, 2001), partial eta-squared (ηp^2) arguably apply more to repeated-measures ANOVAs as it more closely approximates what eta-squared would have been for the factor had it been a one-way ANOVA (Dunlap et al., 1996).

[1] Data, syntax available for access at https://tinyurl.com/y7j68l8u

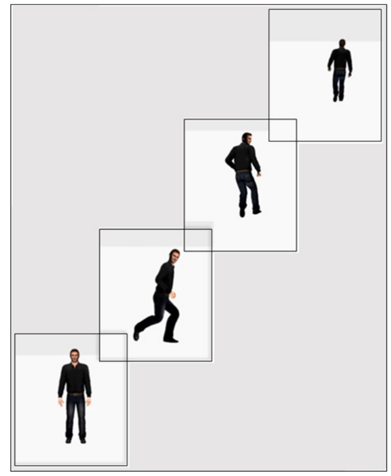

Figure 2: Virtual agent walking away (Distance: Far, Direction: Away, Speed: Slow, Gaze: Direct).

Materials

Participants were presented 16 different randomized videos on Qualtrics, which included virtual agent animations of the unique combinations of the 4 categories of Social Kinematic cues. Please refer to Figure 2 for an example of a stimulus condition. We further elaborate on the construction of this stimuli below. After viewing the 16 stimuli videos, participants then provided ratings on the likelihood that the above visual stimuli would involve a DIAMONDS situation on a graphical slider that ranged from 0-7. The decision to use a graphical slider as opposed to a conventional Likert-scale was to mitigate the reliability issues that arise from forcing participants to select whole integers as values of judgment. An example of an item that addressed the Duty element of the DIAMONDS was, "*How likely is this situation to involve work, tasks, or duties*?" This wording of the items were derived from Serfass and Sherman (2015).

Stimuli We used virtual agents as stimuli because we felt that virtual agents could reliably represent various forms of human movement. We built visual stimuli used in this experiment using the animation software *Smartbody* (Thiebaux et al., 2008), an open source modular framework for animating virtual humans and other embodied characters developed by the USC Institute for Creative Technologies. Smartbody is an engine that allows BML behavior descriptions to be converted into real-time 3D character animations (Shapiro, 2011) (e.g., walking/jogging, facial expressions, gaze, gestures, head nods), making it an ideal platform to generate human-like movement animations for the current study. For the purposes of this study, we adapted a GUI of Smartbody that enabled simple manipulation of the relevant movement cues (Distance, Direction, Gaze, Speed). See Figure 2 for a sample of the study stimuli.

Results

Multivariate Effects

Multivariate main effects were observed for all 4 cues, but we will not report individual main effects due to space limi-

Table 1: Univariate Main Effects (F scores)

DIAMONDS	(Distance)	(Direction)	(Speed)	(Gaze)
Duty	.000	66.646***	3.793	.334
Intellect	.368	98.907***	1.395	2.382
Adversity	2.221	63.851***	1.7	2.076
Romance	.824	99.859***	.017	1.111
Positivity	7.442**	194.279***	3.898	1.337
Negativity	.044	137.069***	.177	6.295*
Deception	.224	123.011***	1.096	6.590*
Sociality	8.279**	133.526***	.408	6.768*

* $p < .05$, ** $p < .01$, *** $p < .001$

tations. 2-way multivariate interaction effects were observed for Gaze and Direction ($F(8, 189) = 2.734$, $p = .007$, Wilks' $\Lambda = .896$, $\eta p^2 = .104$), and Speed and Direction, ($F(8, 189) = 5.913$, $p < .001$, Wilks' $\Lambda = .800$, $\eta p^2 = .2$) . Significant 3-way multivariate interaction effects were observed for Distance, Speed, and Direction, $F(8, 189) = 3.81$, $p < .001$, Wilks' $\Lambda = .861$, $\eta p^2 = .139$). Finally, there was a significant 4-way interaction effect of Distance, Speed, Gaze, and Direction, $F(8, 189) = 2.641$, $p = .009$, Wilks' $\Lambda = .899$, $\eta p^2 = .101$. While a discriminant analysis may better reveal how the 4 categories differ from each other in multivariate terms, this was not feasible due to the repeated measures design of the study and data collection.

Univariate Effects

Univariate main effects Among the 4 kinematic variables, *Direction* (towards, away) demonstrated the strongest direct effects on social judgments. Univariate main effects of Direction were observed for all 8 DIAMONDS (See Table 1 for reporting). Post hoc test using the Bonferroni correction revealed that movement Away was associated with Adversity, Negativity, and Deception whereas movement Towards was associated with Duty, Intellect, Romance, Positivity, and Sociality. Here, we observe an alignment of positive and negative judgments with towards and away direction, respectively.

Univariate main effects of *Distance* were observed for Positivity, $F(1, 196) = 7.44$, $p = .007$, and Sociality, $F(1, 196) = 8.28$, $p = .004$. A post-hoc test using the Bonferroni correction revealed that participants judged the virtual human to be more Positive and Social when he was near as opposed to far.

Univariate main effects of *Gaze* were observed for Negativity, $F(1, 196) = 6.30$, $p = .013$, Deception, $F(1, 196) = 6.59$, $p = .011$, and Sociality, $F(1, 196) = 6.77$, $p = .01$. A post-hoc test using the Bonferroni correction revealed that judgments of Direct Gaze were significantly greater than judgments of Averted Gaze for Negativity, Deception, and Sociality. No univariate main effect of *Speed* was observed (See Table 1).

Univariate 2-way interaction effects A univariate 2-way interaction effect of *Distance-Speed* was observed for Mating (Romance), $F(1, 196) = 4.39$, $p = .037$. A univariate 2-way interaction effect of *Direction-Speed* was observed for Intellect, $F(1, 196) = 7.94$, $p = .005$, Adversity, $F(1, 196) = 7.72$, $p = .006$, Romance, $F(1, 196) = 9.46$, $p = .002$, Positivity, $F(1, 196) = 22.03$, $p < .001$, Negativity, $F(1, 196) = 23.12$, $p < .001$, Deception, 38.29, $p < .001$, and Sociality, $F(1, 196) = 7.82$, $p = .006$. A univariate 2-way interaction effect of *Gaze-Direction* was observed for Adversity, $F(1, 196) = 5.88$, $p = .016$, Negativity, $F(1, 196) = 7.67$, $p = .006$, Deception, $F(1, 196) = 17.40$,$p < .001$, and Sociality, $F(1, 196) = 7.43$, $p = .007$. No other 2-way interaction effects were observed.

Univariate 3-way interaction effects A univariate 3-way interaction effect of *Distance-Gaze-Speed* was observed for Positivity, $F(1, 196) = 5.73$, $p = .018$, Negativity, $F(1, 196) = 8.85$, $p = .003$, and Deception, $F(1, 196) = 3.89$, $p = .05$ – albeit marginally. A univariate 3-way interaction effect of *Direction-Distance-Speed* was observed for Adversity, $F(1, 196) = 13.77$, $p < .001$, Positivity, $F(1, 196) = 7.80$, $p = .006$, Negativity, $F(1, 196) = 6.91$, $p = .009$, and Deception, $F(1, 196) = 21.76$, $p < .001$.

Multi-level Mean Ratings Thus far, we have seen that there are significant main effects, as well as 2-way and 3-way interaction effects. Although we found no 4-way interaction effects, below we present high and low mean scores across each Kinematic feature (4-way) for each DIAMONDS. This may provide some insight into the physical characteristics of each situational variable in an itemized format. Due to space constraints, we will only report on Duty and Romance here as exemplars. Complete results for the other DIAMONDS are available upon request.

Duty The highest values for Duty were observed for Moving Towards, Fast, Direct Gaze, from a Far Distance (m = 2.738). Duty was generally associated with movement Towards, and there appear to be little effect of the nature of the Gaze, corroborating the lack of Gaze-related results above. The lowest value for Duty was observed for movement Away, Slowly, with Averted Gaze, from a Far Distance.

Romance None of the 16 virtual human conditions were rated highly in terms of Romance, raising a unforeseen limitation of the stimuli in that it only involves one virtual human character. Among the 16 conditions, the highest rating for Romance was observed for movement Towards, Quickly, with Averted Gaze from a Near Distance (m = 2.25). The lowest rating for Romance was observed for movement Away, Quickly, with Direct Gaze from a Far Distance (m = 1.09).

Discussion

The current study examines the intersection of Social Kinematic cues and situational social meaning using virtual agents. Analyzing the simultaneous perception of binary levels of Distance, Direction, Speed, and Gaze, we find strongest effects for directional movement (towards, away) on social judgments of multiple situational items, relative to distance, speed. Specifically, away direction was associated with negativity while towards direction was more associated with positivity (although more ambiguously defined), consistent with prior connections of physical directional movement to approach-avoidance motivation systems (Elliot & Covington, 2001). Gaze was also more impactful on social judgments than more mechanistic cues like Distance and Speed.

We present this work as an initial exemplar of potential methodology to analyzing multiple cues in combination. Although space constraints limit our complete reporting of the analysis of cue combinations, the study considers all possible combinations of the identified social kinematics categories. We reiterate that the situational context for the social kinematic stimuli was intentionally designed as ambiguous and ill-defined (e.g., blank backdrop, no narrative description). The objective here was to control for any potential confounds to individuals' judgments of the social kinematic cues. Inevitably however, there were indeed implicit confounds to judgments (e.g., gender, race, appearance, attire) that we discuss further in the limitations section below.

Limitations

There are several limitations of the present work that should be addressed. First, the present study is quite minimal in terms of combinatorial analysis, and future work should account for both more cues and levels of cues. For example, our failure to account for Gesture presents a significant concern as a framework of socially impactful movement cannot exclude gesture. That said, we plan to account a separate typology for gesture kinematics in our forthcoming work.

Second, we note that the stimuli used in the present study was entirely based on one male virtual human. The gender and the appearance of the virtual human would certainly impact different participants' (i.e., a male or female participants') social judgments, and as such future work should work to eliminate gender, appearance, and race confounds. Relatedly, in our design of the experiment, we failed to prepare for the general creepy nature of an expressionless virtual human walking and running in different patterns. Again, facial expression and appearance would have a clear impact of inferred social meaning. These effects may potentially be mitigated in future work by blurring faces, by designing animated silhouettes (rather than complete virtual humans), or by introducing different variations of expressions as additional conditions.

Third, our use of the DIAMONDS measure is not without its flaws. Most notably, some of its dimensions, such as positivity and negativity, should be defined as higher-order levels that nests on top of the other dimensions. We also suggest expanding on the DIAMONDS to a measurement more appropriate for the perception of nonverbal cues.

Implications

While this work contributes our understanding of social meaning construction and human movement, we also feel it contributes to the development of autonomous virtual agents. Indeed, the future goal of this project is to build a framework for both the generation and perception of socially meaningful virtual agent movement.

A pressing issue in both psychology and agent-modeling communities is the inability to account for the wide variance in human variability and individual differences. Added to this is the further complexity of changing human goals in response to sequential turn-taking. Therefore, in our future work, we plan to develop a computational model of this social complexity in order to ultimately design intelligent agents capable of responding dynamically to a wide range and combination of cues, in a wide range of social situations.

Conclusion

In this paper, we present a systematic explication of Social Kinematics, which is empirically based on developmental psychology (Heider-Simmel), Laban Movement Analysis, and nonverbal behavior. We also introduce a framework for studying inferred situational social meaning that includes narrative components, behavioral measurements, and approach-avoidance motivation systems. Centrally, this paper explores the mapping of Social Kinematics onto situational social meaning using artificial agents as stimuli.

Our forthcoming work will focus on a more systematic use of virtual agents to examine the perception of different nonverbal cues. Namely, we plan to design contextualized virtual scenarios where participants may engage in a more dynamic interaction with the virtual agent. Such a virtual agent model would adjust its nonverbal behavior according to a specific situational parameter (i.e., less creepy), and attempt to induce greater sense of such a parameter in the human subjects (i.e., feeling more comfortable), which we would evaluate with a questionnaire (more refined than the DIAMONDS). Using such a virtual agent model would enable a more refined "tuning" of social parameters as experimental stimuli, aiding not only the development of research into human kinematics, but also the development of an autonomous virtual agent systems.

Ultimately, the current paper provides a potentially useful framework that has relevance for social robotics and agent-based modeling fields, where it is desirable to develop social agents that can enact social kinematics. By the same token, a taxonomy of social kinematic events, and results regarding their social significance are of importance to cognitive science researchers as well. As humans, we constantly use theory of mind to infer social meaning from other individuals' cues. Our vision for our future work is to extend such meaning construction into machine perception of social kinematics in intelligent agents.

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