## Title
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# Identifying Kinematic Cues for Action Style Recognition

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**Abstract**

Recognition of emotional states from other's actions is one of key capability for smooth social interaction. The present study provides a computational-theory-level analysis on which feature may take a crucial role in recognition of emotional attributes in human actions represented as point-light display. Lead by the previous theoretical works and empirical findings, the velocity and acceleration profile was investigated as a major feature of emotional attributes classification. The results showed that emotional attributes in actions as well as action types could be identified by covariance of velocity profiles among multiple body parts. Since, despite different velocity profiles in different actions, these features for emotional attributes were found commonly in multiple different actions, it suggests that the action styles may be mediated by an information channel parallel to action types per se.

**Keywords:** Action style recognition**;** biological motion; emotion; social cognition.

## Introduction

Our bodily motion is coherent, smooth and effortless. From bodily motion, we perceive other's state such as mood, emotional expression, and intention (Blake & Shiffrar, 2007). Perception of other's state takes a crucial role in social context. Although most of us can easily "read" what others intend to do through their actions, there is a significant gap from the physical motion – a set of trajectories of multiple body parts with a large degree of freedom (Bernstein, 1967). Recognition of motion is vitally important to any animal kinds. Detection of another animal, possibly a pray, a predator, or a conspecific, and the following detailed identification what it is and how it may behave is essential to take an emergent actions to it (Johnson, Bolhuis, & Horn, 1985). Humans are social animals. Not surprisingly, our visual system is highly specialized to recognize others' state. The present study aims to provide a computational-level description on how people recognize emotional status in others' actions.

### Perception of biological motion

How do we recognize implicit patterns in different styles of actions? The past experimental literature has explored capacity of motion perception using point-light displays (Johansson, 1973) in which the point-lights attached in major joints are only visible in the dark background (Figure 1a). Thus the available information is point-wise kinematic motion in multiple body parts. Despite of the limited information, people can recognize identity (Troje, Westhoff, & Lavrov, 2005), gender (Kozlowski & Cutting, 1977; Troje, 2002), emotions (Pollick et al., 2001; Atkinson; 2009; Hobson & Lee, 1999), dynamics such as the weight of a lifted object (Bingham, 1987) of actions from point-light displays.

Not only demonstrating human capacity, the studies using point-light display have suggested features extracted in action perception. Accumulating empirical studies on action perception have suggested that velocity and its higher order derivatives in a single or multiple body parts as one of major correlates to emotional attributes in actions: duration of action (Pollick et al., 2001), velocity (DeMeijer, 1989), acceleration (force or the second order time derivatives) (Chang & Troje, 2008; 2009) and jerk or the third order time derivatives (Cook, Saygin, Swain, & Blakemore, 2009), pairwise counter-phase oscillation (Chang & Troje, 2008; 2009). In particular, we highlight the contribution of the higher order derivatives of velocity and importance of its covariational structure. Of relevance, Chang & Troje (2009) found that, not one of either but a pair of feed motion was a major cue for discrimination of walking direction.

### Past computational models on action recognition

Consistent to these empirical findings, most of the theoretical approach works on some kind of statistical regularities among motion profiles. According to a recent review (Troje, 2008), perception of biological motion has the multi-level processing on local and global motion properties. The feature processing consists of four layers from early (low-level) to late (high-level) processing: life detection, structure-from-motion, action recognition, and style recognition. The system detect autonomous agent, and construct body structure from its detailed analysis, then is followed by more detailed action analysis.

A couple of computational models are available for structure-from-motion and action recognition (Giese & Poggio, 2003; Lange & Lappe; 2006), and a few for post-action-recognition-level style perception (Troje, 2002; Pollick, Lestou, Ryu, Cho, 2002; Davis & Gao, 2004) in vision science. In the model of structure-from-motion and action recognition, the model identifies body structure and subsequently actions from the pixel-based visualization of point-light displays. In Giese & Poggio (2003), the model was built based on neuro-physiological findings on visual cortex, and was applied to recognition of action types and action direction in normal, masked, or scrambled point-light displays.

While, the post-action-recognition-level models for style perception typically assume the either/both 2D or 3D point-light on the major joints and also which action is to be executed is readily available prior to the recognition of action style (Troje, 2002; Davis & Gao, 2004; Pollick et al., 2001). For example, Troje (2002) have proposed a computational model of gender identification in gait presented as point-light display. The model was built upon the three stages: First a set of postures is encoded based on Fourier decomposition, the low-dimensional projection of extracted features is obtained by principal component analysis (PCA), and then it is fed to classifier (as a similar model, see also Davis & Gao (2004)).

**Simple, transparent, yet general model**

Although the previous theoretical works have offered successful pattern recognizer for biological motion, there are three shortcomings. First, most of the studies have been closed in one special type (or its slight variant) of action which often has a unique constraint such as periodicity (e.g., walking, running; e.g., Troje, 2002). Second, related to the first point, a limited number of body parts specialized for each action tends to be (e.g., arm movement for tennis swing (Pollick et al., 2002) ). Although not all the model is specialized, in turn, such a generalized model typically loses transparency of mechanism as a cost of generality (For example, multi-layer physiologically-plausible model, Giese & Poggio, 2003). One of drawback of complex models (using nonlinear filters or feature decomposition technique such as Fourier decomposition and PCA) is that the estimated parameters do not necessarily offer interpretation on which natural features are informative such as body parts and time course (Pollick & Paterson, 2008). Moreover, such model often outperformed human recognition (Troje, 2002; Davis. & Geo, 2004; Pollick & Paterson, 2008) rather than explaining use of features in human recognition.

**The theoretical assumptions in the model**

In the present study, we employed the simplest possible framework – a variant of linear regression – in order to characterize the motion cues in whole body interaction for multiple types of actions and emotional attributes. The model has the three major assumptions as follows. (1) The major joint (point-light) is specified and readily available prior to action and style recognition as well as the previous post-structure-from-motion models. Specifically, the point-light coordinate was directly fed to the model. (2) The velocity profile (and its higher-order derivatives) is supposed a primary source of information for style recognition. (3) The model integrates local (single-joint motion) and global (multi-joint motion) in form of linear combination. This is simply implemented as linear regression in which the best linear combination of them was estimated by optimization of recognition/classification performance.

On the other hand, we *do not* assume that action is specified prior to recognition of action style, instead we rather expect to find generalizable features of action style common in multiple types of actions. Since people can recognize different styles in unconventional actions (Moore, Hobson, & Lee, 1997; Hobson & Lee, 1999), a model for human biological motion is required to be general for multiple actions.

Specifically, in the present study, we analyzed the human bodily actions while the actors were given different emotional contexts (Ma et al., 2006). These actions are experimentally manipulated which emotional context was intended to be under each action performance. Given such a set of human actions, our first goal is to recover the latent emotional attributes which the actor intended to hold (or so experimentally manipulated) from the physical motions. By doing so, we describe how the emotional attributes are expressed in the different bodily actions. More specifically, we focus on the following questions: Is it possible to find a general features regardless of different types of actions? If so, which types of features take crucial roles?

## Biological motion library

Ma et al. (2006) have created an open-access biological motion library, consisting of data recorded from a motion tracking system (point-light actors: Figure 1a). The dataset contains 30 naïve actors each performing 5 actions (walk, knock, lifting, throw, and combinations of the four actions) in 4 emotional contexts (angry, happy, sad, and neutral) (see Ma et al., 2006 for more detail). Each action was performed after the subject was given a background story manipulating the emotional context how the subject is supposed to perform the action. In the present study, we used a subset of actions mainly using right hand, i.e., knock, lift, and throw. As an example, the joint angle of right arm and its angle velocity while 5 repeating the same actions is drawn in 1b.

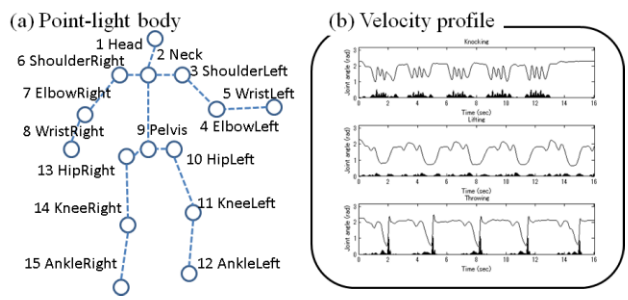


Figure 1: (a) Point-light actor (no link in the model and behavioral test), (b) A temporal profile of right-hand-elbow-shoulder joint angle (solid line) and its velocity profile (black) in 5 repeating knock, lift, and throw actions.

## Model of Emotion Recognition from Actions

We analyzed a subset of the data from biological motion library (Ma et al., 2006). This subset included 15 male and 15 female actors performing 3 different actions (knock, lift, throw) in each of 4 different emotional contexts (neutral, angry, happy, sad). Although the model was trained with actions with neutral emotion as well as actions with emotional attributes, only the three non-neutral emotions were used in the test to facilitate comparison to behavioral data. The additional neutral actions in the training data give the model a chance to learn actions in emotionally neutral context which human subjects have experienced out of laboratory experiment. Each action in each emotional context was repeated 5 times on each of 2 trials, producing 3600 actions in total.

**Features: covariance of velocity, acceleration, and jerk.** In order to implement previous theoretical findings regarding velocity profiles as a cue for biological motion perception, we used the velocity, acceleration, and jerk covariance profiles to identify actions and emotions. Each of these was used to define features for the regression model. Features came in two kinds: local and global. For instance, variance of acceleration is a local motion property (single-point motion) that captures smoothness of motion over an interval. The covariance of acceleration between multiple points is a global motion property that captures the degree of temporal coordination between two body parts. Variance/covariance was evaluated for each action defined by joint-angle of right arm (see also Ma et al., 2006 for details). We used a nested model structure to identify the contribution of each kind of information to action and emotion identification. The simplest model was a velcocity-only model that included only the single-point variance and two-point covariances for each joint. This model was subsumed by an acceleration model that also included acceleration variance and covaraiance, and both were nested in a model that included jerk variance/covariance information. Since, at each moment, velocity and acceleration of 15 body parts were obtained, 15 variances and 105 covariances were obtained for each action. Thus, a total 120, 240, or 360 dimensions across pairwise body parts were used for classification in the Velocity, Acceleration and Jerk models, respectively. Because it produced the most parsimonious fits to behavioral data, the Acceleration model was analyzed most extensively, and is the model discussed if a different model is not mentioned specifically.

**Classification with automatic dimension reduction**

These normalized variance and covariance features were used to classify emotions and actions using a multi-class sparse logistic regression model (Yamashita et al., 2008). Model parameters were estimated in a hierarchical Bayesian framework, which penalizes parameters that do not contribute significantly to improving prediction. This is done with a sparsity that reduces the likelihood of the model in proportion to the number of non-zero parameters (*w*) multiplied by a scaling parameter λ (Figure 1c for its graphical model). Specifically, the probably of each action *i* belonging to class *k* $P(y_{ik})$ follows the multinomial distribution with probability represented as logistic function of linear combination of the given features $x_{ij}$ for data *i* of dimension *j* with the weights $w_{jk}$ as follows.

$$p(y_{ik}) \propto \left(1+\exp\left(\sum_j x_{ij} w_{jk}\right)\right)^{-1} \quad (1)$$

The loglikelihood of class of data given by Equation 1 combined with the prior probability on the weights *w* is maximized. The sparseness prior is given as follows.

$$p(w_{jk}) \propto \sqrt{\lambda_{jk}} \exp\left(-2^{-1}\lambda_{jk} w_{jk}^2\right)$$

$$p(\lambda_{jk}) \propto \lambda_{jk}^{-1}$$

where weights follows the gamma distribution with the hyper parameter $\lambda_{jk}$ which follows a fixed-parameter gamma distribution (Jeffrey's prior). This prior prefers zero-value weights, and thus penalize non-zero weights without sufficient information to classification of the given data.

Thus, without any free parameter to adjust, most of weights on non-relevant dimensions were supposed to be excluded from the model on course of optimization.

The each action in the dataset is randomly assigned either training or test samples. The 3300 training samples were used to estimate the parameters in the classification model, and its performance with the 300 test samples was evaluated. The reported results were averaged across 10 randomly generated sets of test/training samples.

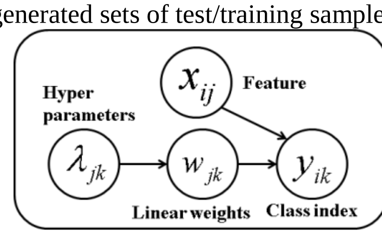


Figure 2: The sparse logistic regression linking the velocity features to given emotion/action class.

**Classification performance in the model**

The average correct classification of the Acceleration model with velocity and acceleration profile as features was 97.5% for action types and 69.73% for emotion classes at 33% as chance level of both action and emotion classification. The response patterns of the model in emotion classification were shown at the bottom panel in Figure 2. In order to evaluate the model's prediction on the action/emotion classification, we conducted the behavioral study on action/emotion classification. The detail of the model's prediction would be discussed with the behavioral data.

## Behavioral study: action/emotion classification

In order to test the prediction of the proposed model, we run behavioral experiment in which adult participants were asked to classify the type of actions and emotions given human actions presented as a point-light display. A subset data from the biological motion library was used as stimuli.

**Participants**

10 graduate students at Indiana University were recruited.

**Material**

Action-emotion stimuli were sampled from the biological motion library (Ma et al., 2006). Nine pairwise combinations of 3 actions (knock, lift, and throw) and 3 emotions (angry, happy, sad) were sampled from each of 3 selected actors. This yielded 27 video clips in total. The viewing angle was fixed to look down the actor from actors' left side, so that the view capture the both front and side aspects of actions. From this fixed angle, point-lights from different joints rarely overlapped.

**Procedure**

The experimental procedure consisted of two separated phases. In familiarization phase, 9 video clips (3 actions by 3 emotions) which were not used in the following phase were presented on a computer monitor simultaneously. Each was accompanied by a label identifying both the action and emotion in the clip. Participants were told that they would be asked to categorize similar clips by action and emotion, and that they should watch the clips until they instructed to watch the clips until they were satisfied that they felt they could do so.

A test phase followed immediately after the familiarization phase. Each participant watched a series of 15 second in which a point-light actor performed one of the 3 actions in the style of one of the three emotions. Participants were asked to determine the action and emotion in each video. Presentation of the stimulus on each trial was ended either when the clip ended or when the participant pressed a button to advance to the next trial. The test phase consists of 27 trials, with presentation order randomized by participant. Together, the familiarization and test phases lasted approximately 10 minutes for each participant.

## Results and Discussion

The proposed model provides quantitative prediction on classification of emotional attributes based on statistical structure in velocity profiles. Here we compared classification performance of action and emotion in the human behavior and the models. The correct ratio in action classification was nearly perfect in both human (98.61%) and the Acceleration model (97.5%) to chance level 33%. The correct ratio in emotion recognition was comparably medium level in both human (68.98%) and model (69.73%) to chance level 33%. The result showed the model achieved comparable performance in biological motions in both action and emotion classification.

**Data fitting and comparison of models**

Since the action classification was nearly at ceiling, we analyzed the classification error patterns emotional classification in detail (Figure 3). Figure 3 shows the proportion of responses for each type of emotion. In order to analyze which kind of feature human subjects utilized, we compared the three variant of the models with nest-structure feature sets: *Velocity* model with only velocity profile, *Acceleration* model with velocity and acceleration profile, *Jerk* model with velocity, acceleration, and jerk (up to the third order derivative). The goodness-of-fit for each model was evaluated to what extent human responses in the behavioral data followed a multinomial distribution with the average proportion of responses in each model as parameters. Note that, although the feature set in the models were different, none of the three models were optimized for fitting of the behavioral data (thus no free parameter). Instead they were optimized to classify the emotional attributes in actions. The log-likelihood of data for Velocity, Acceleration, Jerk model were -93.931 ($R^2$ = 0.810), 90.051 ($R^2$ = 0.890), and -89.116 ($R^2$ = 0.900), respectively. The likelihood ratio test revealed significant difference in likelihood of Velocity model from the other two models ($\chi2(1)>3.8807$, $p<0.05$), but did not find significant difference between Acceleration and Jerk model ($\chi2(1)$= 0.7479, p=0.33). This result of model comparison suggested that velocity profile alone was not sufficient to capture behavioral patterns, but velocity and acceleration profile might be sufficient since the additional jerk profile made little additional contribution for data fitting. Therefore, hereafter we analyzed the Acceleration model as the representative model.

**Action-specificity of emotion attributes**

Next, we tested the hypothesis that recognition of emotion attributes is specific to each action types. If so, the model trained to classify emotional attributes for each action (*Action-specific* model) would capture behavioral patterns better than the model trained to classify them for all the three actions together. The log-likelihood of Action-specific acceleration model was -90.6381 ($R^2$ = 0.890) which is slightly worse but not significantly different from that of non-action-specific acceleration model ($\chi2(1)$= 0.5871, p=0.444). Therefore, the action-specific model did not necessarily offer a better account for human recognition.

**Classification with only average velocity**

One of largest qualitative difference between human and model was found in the proportion of response “happy” to angry action: human recognizers confused angry with happy more than with sad, whereas the model recognizers confused it with sad more than happy. According to the post-experimental interview to the participants, many of them reported that they relied on average velocity of actions. Typically angry actions tended to be fast, sad actions were slow in the current stimuli, and happy ones were in the middle of them. This may be a potential reason why for human perceiver angry actions tended to be confused with happy ones rather than with sad ones, and also the model did not included as its features for classification.

Therefore, in order to evaluate the contribution of average velocity, we performed additional analysis. A past study has reported that the average velocity, or duration of from beginning to end of action, (and its correlated factors such as duration) was one of major correlates to subjects’ rating of emotion attribute (Polllick et al., 2001). Indeed, we found the angry actions were fast and sad actions tended to be slow on average in the data used in the present study. The four-way ANOVA on the factor (emotion types, action types, repetition, and trial), revealed the significant main effect of all the factors but trials ($p<0.01$).

However, the average velocity of the actions alone was not enough for classification of action style. The correct ratio using the average velocity, duration, peak velocity of each action was 35.9% (chance level 25%) which was not comparable to human performance (68.98%). Even after we classify the subset of data separate for each action, the classification performance did not improve significantly (Average of three actions: 36.4, Knock: 34.1, Lift: 38.0%, Throw: 37.1% for the chance level 25%). This result suggested the average velocity of actions alone could not fully explain the action style recognition.

In sum, the current model-based analyses suggested that the covariance profile of acceleration in multiple body parts carried significant amount of information on emotion attributes in actions. Despite of very different velocity profiles in three actions, knock, lift, and throw, the classification of emotion regardless of the actions was as successful as action-specific classification. This result suggested that, to some extent, emotional attributes in actions were more general rather than specific for each action.

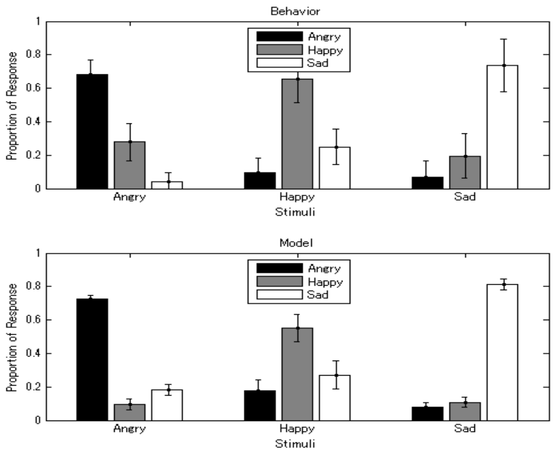


Figure 3: The response patterns for each emotion type in human subjects (upper panel) and the model (bottom panel).

**Distributed cues in emotion recognition**

Next, we analyzed the effective feature dimensions for each emotion attribute in the Acceleration model. In the sparse logistic regression, the fewest possible feature dimensions were automatically selected among all the given dimensions. The selected dimensions, variance and covariance of acceleration profiles, were supposed to be a spatiotemporal "template" informative to action/emotion attributes. Thus we analyzed which features are specified for each of emotion attributes. Figure 4 depicted the inter-connection between body parts which were identified as significant features for emotion discrimination (see also criterion of the dimension selection in the model). In each panel of Figure 4, the thin and thick lines indicate covariance of velocity and acceleration for a pair of body parts respectively which is also coded by intensity in the adjacent matrix. The number of effective dimensions for velocity/acceleration and local (variance)/global (covariance) was shown at the bottom right panel.

We found the numbers of effective velocity dimensions (either local or global) were consistent with the average velocity: the largest number of effective dimensions in angry actions which tended to be performed fast, meanwhile the smallest number of them in sad actions which tended to be performed slow. Also the total number of effective dimensions for each action was consistent to the classification performance (Figure 3): the model found fewest effective dimensions for happy actions and had lowest accuracy in identifying them. Overall, we found more global features (pairwise covariance) than the local features (single-point variance). This result suggested that the emotional attributes were distributed rather than specific to a small number of body parts. Since these patterns found in the present model were directly interpreted as those on body parts or their relationship, they would offer a specifically testable prediction on which body parts may be potentially informative.

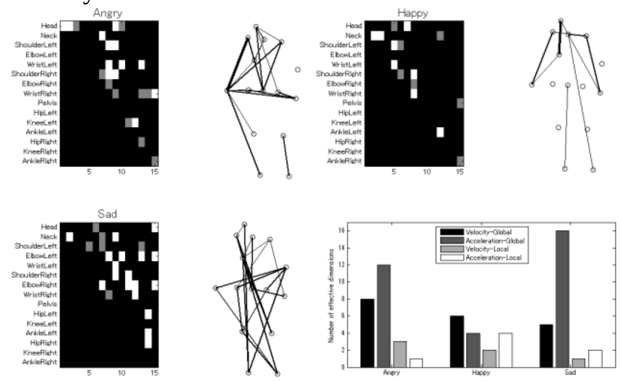


Figure 4: The variance/covariance in velocity profile significantly relevant to each emotion attribute mapped on a body scheme. The white and gray cell indicates effective variance/covariance of velocity and acceleration, respectively. No lower triangle cells were presented due to its symmetricity. The bottom right panel showed the number of effective dimensions for each emotion attribute.

## General Discussion

In the present study, we provided a computational model which specifies characteristic kinematic features for recognition of emotional attributes in actions. Following the lead of the past studies, we analyzed the velocity profile with special attention. Classification with covariance of velocity and acceleration profile among multiple joints showed comparable performance as good as human classification. Moreover, by comparing multiple models trained with different feature types, it suggested that (1) velocity alones was not sufficient but combined with acceleration or higher order derivatives might characterize the human emotion recognition, and (2) there may be common emotional attributes invariant to action-specific motion profiles.

**Action style as parallel process rather than hierarchy**

The present analysis showed that, based on covariance of velocity profile across whole body, emotion attributes may be characterized beyond specificity of each action. However, recent review on action recognition offers a contradictory view to the present study: recognition of action style needs action recognition in prior to it. According to a recent review (Troje, 2008), perception of biological motion is multi-level processing on local and global motion properties. The feature processing consists of four layers from early (low-level) to late (high-level) processing: life detection, structure-from-motion, action recognition, and style recognition. Once both agent and action are identified, pattern recognition at a "subordinate" level (Rosch, 1988) helps to retrieve further information about the details (i.e., action style) of both.

In the present study, we propose an alternative view on action style perception: The emotion attributes can be identified with or without pre-specification of action types.

In the present analysis, we found that the model without action-specific features can account for behavioral classification performance as well as that with action-specific features. Therefore, we speculate that action style is "parallel" process rather than hierarchical one to action recognition which may be coded independently from the action types.

**Future works**

One of the future directions is to extend the behavioral study so that we can evaluate subjects' attention to body parts and its time course using an additional measure (e.g., eye movements). The extended behavioral study would allow us to directly test the model's detailed prediction about which body parts and their relationship may be informative to action/emotion classification (Figure 4).

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