Methods for Quantifying Emotion-Related Gait Kinematics

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Abstract. Quantitative models of whole body expressive movement can be developed by combining methods form biomechanics, psychology, and statistics. The purpose of this paper was to use motion capture data to assess emotion-related gait kinematics of hip and shoulder sagittal plane movement to evaluate the feasibility of using functional data analysis (FDA) for developing quantitative models. Overall, FDA was an effective method for comparing gait waveforms and emotion-related kinematics were associated with emotion arousal level.

Keywords: Whole Body Interaction, Motion Capture, Functional Data Analysis, Affective Computing.

1 Introduction

Integrating expressive whole body behavior into computer applications is an important feature for emerging applications ranging from the gaming industry to virtual environments. Many of these applications will need to recognize and produce emotionally expressive behavior for natural interaction between human and computer. Effective integration of these capabilities requires quantitative models of expressive behavior. To date, relatively few studies have used quantitative methods to investigate characteristics associated with expressive movement. Thus, the purpose of this paper is to demonstrate one possible approach to quantifying the effect of emotion on joint angular kinematics.

The approach presented in this paper for characterizing expressive behavior is multidisciplinary, combining methods from biomechanics, psychology, and statistics. From the field of biomechanics, the use of motion capture technology is an established method for gathering quantitative movement data. With this method, passive retro-reflective markers are placed on specific anatomical landmarks on the body and the position of each marker is tracked using high-speed video cameras. The centroid position of each marker is calculated for each instant in time. The three-dimensional coordinate data are used to demarcate body segments that are linked to form a representation of the body; each segment represents a bony segment of the musculoskeletal system. Therefore, motion capture can be used to describe body position and how it changes over time from three-dimensional coordinate data.

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Motion capture is an effective method for describing body movement, but when the aim is to characterize expressive movement, methods from psychology can help ensure that the motion data contains the expressive signal. In brief, to identify emotion-related movement characteristics, the emotion signal must be in the motion data analyzed. Therefore, the emotion must be felt by the encoder and recognized by observers. Evaluating felt emotion is important for two reasons. Firstly, recent fMRI studies suggest a neurological basis for emotion affecting body movements in characteristic ways [1, 2]. Secondly, the quantitative difference, if any, of movements between felt and recognized emotions remains to be studied. Consequently, for studies that assume neurobiological changes due to emotion, it is especially important to ensure that the experience of emotion and associated bodily changes are captured [3]. Additionally, identifying trials that communicate the target emotion increases the probability that the data analyzed are representative of the actual emotion. Thus, validated methods from psychology can be borrowed for inducing and evaluating felt emotions as well as identifying motion stimuli that communicate target emotions.

The purpose of this paper is to provide a framework for characterizing emotion-related whole body movement and to demonstrate one potential statistical technique for quantifying emotion-related movement characteristics. First, the framework used for capturing emotion-related kinematic data is discussed. Second, functional data analysis methods are described. Finally, the results and conclusion of our analysis are presented.

2 Framework for Collecting Motion Data

Established methods from psychology can help ensure that motion data included in quantitative analyses contain the emotion-related signal. This section describes 1) the protocol used to capture motion data while participants experienced one of five target emotions, 2) the method used for evaluating felt emotion, and 3) the use of a social consensus paradigm to determine whether observers were able to accurately recognize the emotion portrayals.

Walking was studied because it is a well-documented whole body movement task in biomechanics and it is an emotionally neutral task. Further, studying a single movement task allows the expressive content to be separated from the task so that changes in the kinematics can be attributed to emotion difference. Previous studies have also demonstrated that emotions are recognizable in walking [4], suggesting that characteristics modifications in this task may be associated with specific emotions. Thus, walking is an ideal task to begin exploring the characteristic movement styles associated with specific emotions.

2.1 Motion Capture

The following methods were used to collect motion data, emotion elicitation data, as well as side-view video from walker participants. Further details about the methods used to collect these data are described in [3]. Walkers (n = 42, [5-7]52% female) were recruited from the University of Michigan undergraduate student population. Ages ranged from 18-32 years (20.1 $\pm$ 2.7 yrs.). All participants were able-bodied and no special skills were required. Prior to data collection, participants reviewed a description of the study and signed a consent form approved by the Institutional Review Board (IRB).

Upon arrival, the participants were informed that the study was about the expression of emotion and that video and motion capture data would be recorded during walking. They were informed that their faces would be blurred in the whole-body videos and these videos would be shown to peers in another study.

An autobiographical memories paradigm [5-7] was used to elicit emotions in participants. Participants were given as much time as needed to complete an autobiographical memories worksheet. They were informed that the worksheet was for their use only, to help feel emotions, and would remain confidential. On the worksheet, participants were asked to describe times in their own life when they felt two negative emotions (angry and sad), two positive emotions (content and joyful), and neutral emotion. Using only a few words, they were asked to indicate a) where they were, b) who they were with, and c) what caused the feeling/what was it about? For example, to elicit sadness, participants were asked to recall the following scenario.

> *Think of a time in your life when you felt in despair, for instance, when you felt low or depressed, or felt like you wanted to withdraw from the world.*

After completing the worksheet, participants changed into a special motion capture suit, and thirty-one passive retro-reflective markers (2 cm diameter) were placed on specific anatomical landmarks on the body in preparation for collection of motion capture data. The placement of the markers allowed the body to be demarcated into eight linked segments, each segment representing a bony segment of the musculoskeletal system.

Once the set-up was complete, participants were asked to walk at a self-selected pace approximately 5 meters after recalling a memory from their worksheet. Before each walking trial, the participants read their notes to help recall the specific memory. Memories were referred to as numbers rather than emotions to help ensure that a bias was not introduced. Participants began walking when they felt the recalled emotion as strongly as possible; they did not wait for a cue from the experimenter to begin and they did not have to provide a cue to indicate they were ready to walk. As each participant walked, side-view video and whole body 3-D motion capture data were recorded.

Participants performed three trials for each memory in a block to increase the probability that at least one trial would have usable video and motion capture data and that the target emotion would be felt.

2.2 Emotion Elicitation Evaluation

Subjective experience of emotion was assessed after each walking trial using a self-report questionnaire. The questionnaire included the four target emotions and four non-target, distracter emotions. The non-target emotions were selected for inclusion based on their similarity, in terms of valance and arousal, to the target emotions. After each walking trial, participants rated the intensity with which they felt each of the eight emotions using a 5-item likert scale (0 = not at all; 1 = a little bit; 2 = moderately; 3 = a great deal; 4 = extremely). After each emotion block, the walker was also asked to indicate the trial they felt was their best trial for that memory. The memory order was randomized for each participant.

One observation for each walker for each emotion was selected for inclusion in the final kinematic dataset (42 walkers x 5 emotions = 210 total observations). To be selected for inclusion in the dataset, a trial needed to have usable kinematic data and usable side-view video. If more than one emotion trial met these criteria for an individual emotion portrayal, the trial with the highest score for the target emotion item on the self-report questionnaire was selected. If two or more trials had the same score for the target self-report item, the self-selected best trial was used. If the self-selected best trial was not available, the trial with the lowest scores for all other questionnaire items was selected.

For each of the included walking trials, one gait cycle was selected (Heel strike or Toe off). Motion data was filtered to reduce noise in the signal with a 6Hz low pass Butterworth filter. For each trial the neck, trunk, shoulder, elbow, wrist, hip, knee, and ankle joint 3D kinematics were calculated, in addition to four 2D postural angles. All calculations were completed using C-Motion Visual 3D software package.

2.3 Social Consensus

Side-view video clips from the 210 trials (42 walkers x 5 emotions) selected in the walker protocol were shown to observers in a social consensus study to determine whether the emotion was recognizable. The walkers' faces were blurred to ensure that observers were not using information from facial expression to assess emotion, and the movement clips were looped three times. Two sets of observers (n=60 in each set) from the University of Michigan student population were recruited for participation in each study. Participants (n=60, 48% female) in the Recognition study ranged in age from 18-30 years (20.9 $\pm$ 2.7 yrs). No special skills were required. However, participants could not participate in the social consensus study if they participated as a walker. Displays were considered recognized if the observer recognition rate was greater than the chance recognition rate. Further details about the social consensus study are reported in [8].

3 Functional Data Analysis Methods

Joint angular data from hip and shoulder sagittal plane motion were included in a pilot study to assess the feasibility of quantitatively comparing gait waveforms using a functional data analysis (fda) approach. The object was to characterize the mean behavior in functional form for each emotion.

3.1 Inclusion Criteria

Motion in the sagittal plane for both joints was used in the analysis (flexion / extension). To be included in the analysis, emotion portrayals had to be considered felt by the walker and recognized by observers. For technical reasons, some emotion portrayals were missing motion data. This typically resulted from marker occlusion in the motion capture system. A cubic spline was used to interpolate missing data when

Table 1. Number of trials used in the fda analysis for each emotion for each joint

	Emotion				
	Angry	Joyful	Content	Neutral	Sad
Hip	15	20	22	25	22
Shoulder	16	22	20	17	23

appropriate according to standards in biomechanics. However, trials missing data after applying standard interpolation rules were additionally excluded from this analysis. Because of the strict criterion for inclusion in this analysis, it was particularly important to begin with a large sample size (Table 1).

3.2 Registration

Data were time normalized to ensure that gait cycle events occurred at the same point in time. Fig. 1 illustrates a common problem when analyzing gait data, the amount of time it takes to complete a single gait cycle can vary between trials and between participants. Data registration ensures that this does not confound the analysis. For each emotion portrayal, the data were time normalized to 100 samples per trial.

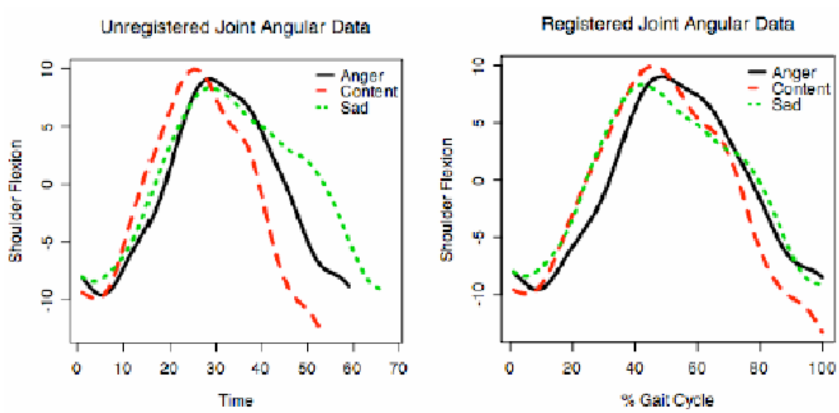

Fig. 1. Comparison of unregistered and registered joint angular data

3.3 Functional Form

A cubic B-spline was used to model the motion data in function form. Although other options such as polynomial functions could have been used to fit the data, these options lack the necessary stability and meaningful interpretations. In addition, using knots to demarcate the waveform into smaller sections can capture subtle features of the waveform. The *fda* library [9] in R version 2.5.0 was used for this analysis.

One primary goal of this analysis was to assess how joint angular kinematics change over time rather than assessing the angular position at the start and end of the gait cycle. Joint angles from human locomotion do not start and end at the exact same angular position. This is expected in human subject data due to naturally occurring variability in human motion resulting from both internal and external factors. However, the variability is expected to be within a small range. A test of the ranges between the start and end angles determined that this variability was not affected by emotion. Therefore, to simplify this pilot study the waveforms were adjusted to start at zero. This allowed us to apply a constraint to the function.

A cubic B-spline regression was used to fit a curve for each emotion group. Knots were visually selected for both the hip and shoulder joints. The object was to obtain a fit with extremely high r^2 (minimum acceptable value was .98), the squared correlation between the fitted values and actual values. In addition to the endpoint constraint, we also assumed that the first and second derivatives at each of the knots matched. A multivariate analysis was used to assess whether emotion affected each of the parameters.

4 Results

The overall results for the hip and shoulder analyses were the same. Three groups emerged based on arousal level: high arousal (anger and joy), moderate (neutral and content), and low arousal (sad).

Four knots were needed to fit the motion data. These knots were visually selected and occurred at 20, 40, 60, and 80 percent of the gait cycle. The shoulder analysis additionally included percent recognition in the regression analysis. Percent recognition was weighted so that portrayals with higher recognition rates had more influence on the fit of the model than those with lower recognition.

The fitted curve for the shoulder joint motion was defined as equation 1. The regression parameters are represented by β_i and the basis functions (Fig. 2) are represented by $\beta_i(x)$, where each is a truncated cubic polynomial.

$$f(x)=\sum_{i=1}^{8}\beta_i \bullet \beta_i(x) . \quad (1)$$

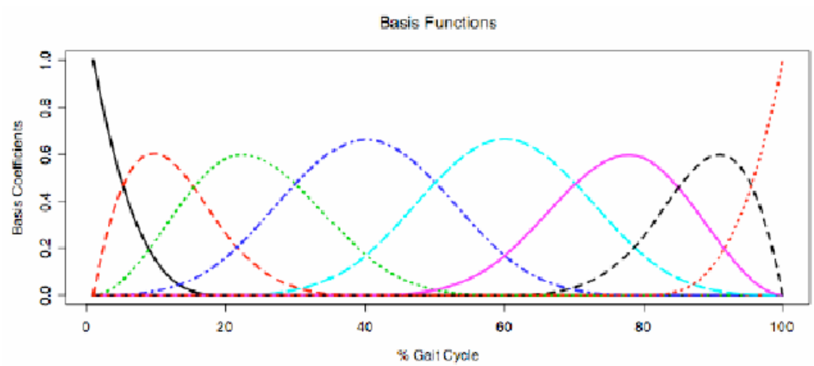

Fig. 2. Basis functions for shoulder joint angular data. Given the use of four knots and three constraints, there were a total of eight parameters.

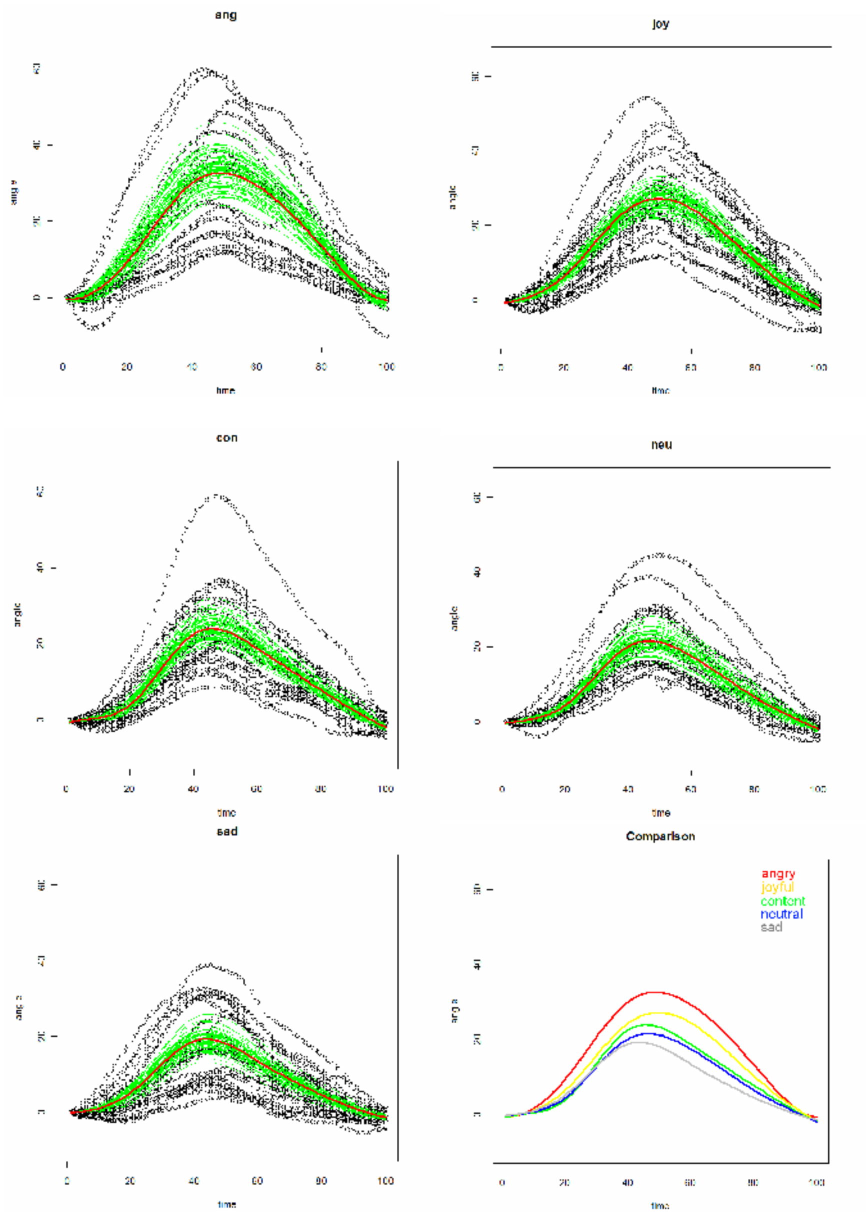

Fig. 3. Mean function for each emotion (red curve) plotted with the actual joint angular data for shoulder motion (black dots). The green curves represent the stability of the mean functional form; narrower bands indicate increased stability. The comparison plot represents the mean functional forms for each of the target emotions.

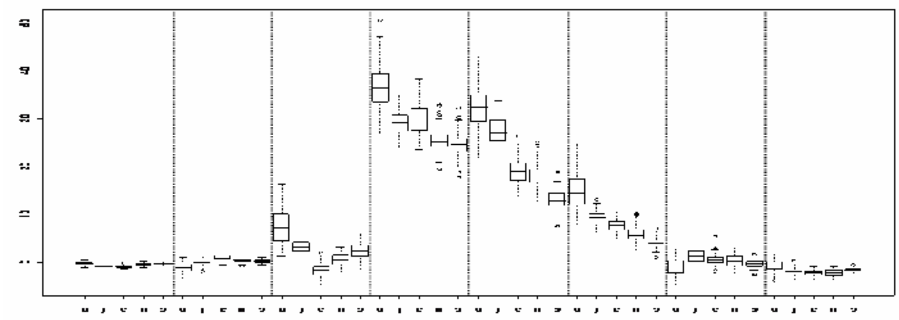

Fig. 4. Side-by-side boxplot of the eight parameters used to model the shoulder motion data. In each boxplot, the order of target emotions from left to right are anger, joy, content, neutral, and sad.

Table 2. First derivative of the shoulder angle position at four points in the gait cycle

	% Gait Cycle			
	20	40	60	80
Anger	1.02	0.63	-0.54	-0.97
Joy	0.76	0.61	-0.49	-0.75
Content	0.68	0.52	-0.55	-0.54
Neutral	0.62	0.46	-0.50	-0.51
Sad	0.63	0.28	-0.51	-0.38

For both joints, the range of motion tended to increase as the emotion arousal level increased (Shoulder Flexion presented in Fig. 3). However, the mean function for anger was the least stable of all target emotions. Stability was tested with a bootstrapping method and is represented in Fig. 3 by the green curves. Visual inspection of the actual angles for all portrayals of each target emotion revealed that anger had the most variability in the movement pattern between individuals. This may have contributed to the decreased stability of the mean function.

The waveforms tended to differ most mid cycle. These differences are represented in a side-by-side boxplot (Fig. 4) that is divided into eight blocks to represent the eight parameters used to model the shoulder motion data. Within each block there are five boxes, each representing one of the target emotions. Post-hoc pairwise comparisons of a multivariate analysis confirmed this effect with the most significant differences between the emotions occurring mid cycle.

In general, increased emotion arousal also corresponded to an increased rate of change in joint angular motion. The rate of change in joint angular motion for the shoulder joint was checked by calculating the first derivatives of the waveforms at the four knots which represent four unique points in the gait cycle (Table 2). With respect to biomechanics, this suggests that arousal is associated with joint angular velocity.

5 Conclusions

The results of this pilot study indicate that joint angular motion can be modeled in function form and gait waveforms can be quantitatively compared. Although the functional form was different for each joint, the differences between emotions were the same for both hip and shoulder kinematics. The high r^2 values (> .98) associated with the fitted models for the joint angular data combined with consistent results for the two joints suggest these findings are robust. The finding that differences were associated with arousal level may be related to changes in gait velocity. Indeed, in a previous study we determined that gait velocity was significantly greater for the high arousal emotions than the low arousal emotion sadness [10].

Based on the results of this pilot study, this method will be applied to assess joint angular data from additional limb and postural gait kinematics. It will also be important to assess the effect of gender, since one limitation of this analysis was that gender was not considered as a factor. Further evaluation is also necessary to determine whether cubic B-splines are the best choice for modeling the joint angular data.

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