



NOTICING EMOTION FROM BODILY MOVEMENT

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ABSTRACT

In this study, we investigate critical emotion-specific posture and movement features, which typically depended only on a small number of joints. The main goal is to minimal representative of emotional display by reducing the amount of joints involved in the movement. Beside to improve the computational efficiency, we can identify the important aspects of emotion expression. This work is inspired by the motor-control concept which defines the involving components of movements that cover only limited set degrees of freedom that are jointly controlled. The approach is based on the basic statistical analysis that is extracted from dynamic motion qualities such as position, velocity, acceleration and jerk. Four discrete categories of emotion, such as angry, happy, neutral and sad were analyzed through actions such as knocking, lifting, throwing and walking. Then, we evaluate the performance from the combination of statistical features extracted using different classifier, k-nearest neighbor (KNN), fuzzy k-nearest neighbor (FKNN), probabilistic neural network (PNN), support vector machine (SVM) and naive bayes (NB) classifier. The findings show that, it is informative enough to consider right arm movement to classify different emotion in actions such as knocking, throwing, lifting and full body for walking.

Keywords: emotion, body movement, action, statistical feature, classifier.

1. INTRODUCTION

Developing tools for identifying emotion in bodily movement is seen as such a challenging area in the research field. This is because emotion can be analyzed from various perspectives. Every part of body movement can be used to transport emotional messages [1, 2]. Thus, procedures in analytically and computationally manageable are very important to successfully identifying an emotion. Over the past decade, many researchers have described aspects of body movements that serve as expressive characteristics of particular emotions [2]. Most of them have taken a "holistic approach" to associate characteristics of the movement and perception of emotion by observing the whole body, for example, the overall level of activity and level of movement including velocity and acceleration [3]. Additional studies have worked in various of techniques for study style variations for movements with different degrees of complexity, including emotional movement styles [4, 5]. However, all of these studies have been addressing the perception of emotional style in a holistic approach, not specifically analyzed which spatiotemporal features are contributing to the perception of individual emotional styles.

The question which spatiotemporal features are important for the perception of emotional styles from body movements already addressed by [6, 7]. Many researchers interested more in studying human action, such as walking. In addition, there are situations where only individual body parts are observable due to occlusion of the rest of the body as presented by [8], [9]. Furthermore, there is interest to display expressive movements on embodiments due to kinematic constraints, are incapable of full-body movements [10]. Thus, we identify that is

important to explore expression and perception of emotion through individual body parts. For this purpose, an analysis of behavior during the execution of emotional movements will be performed for entire action such as knocking, throwing, lifting and walking. We examine a particular aspect of the interpretation of human movement - how affect is perceived by the grouping joint to the particular actions. It is hoped that the features obtained are prominent for categorizing essential information for understanding human movement properties.

The rest of this paper is organized as follows. In Section 2, research methodology is described, including database, feature extraction and classification techniques utilized in this study. Section 3 presents the results and discussion of this work, and conclusions are given in Section 4.

2. RESEARCH METHODOLOGY

a. Database

For this work, a motion-captured database recorded at the Psychology Department, University of Glasgow were used [11]. The dataset contains 30 nonprofessional actors (15 male and 15 female) where each performing 5 actions (walk, knock, lifting, throw, and combinations of the four actions) in 4 emotional contexts (angry, happy, sad, and neutral). Our quoted results are only based on 1200 knocking, 1190 throwing, 1140 lifting and 5007 walking motions. The skeletal structure of the recorded bodies is represented by 15 joints, positioned relative to a world frame. In this study, joint positions were first transformed into a body- local coordinate



system which pelvis as the center of the coordinates origin.

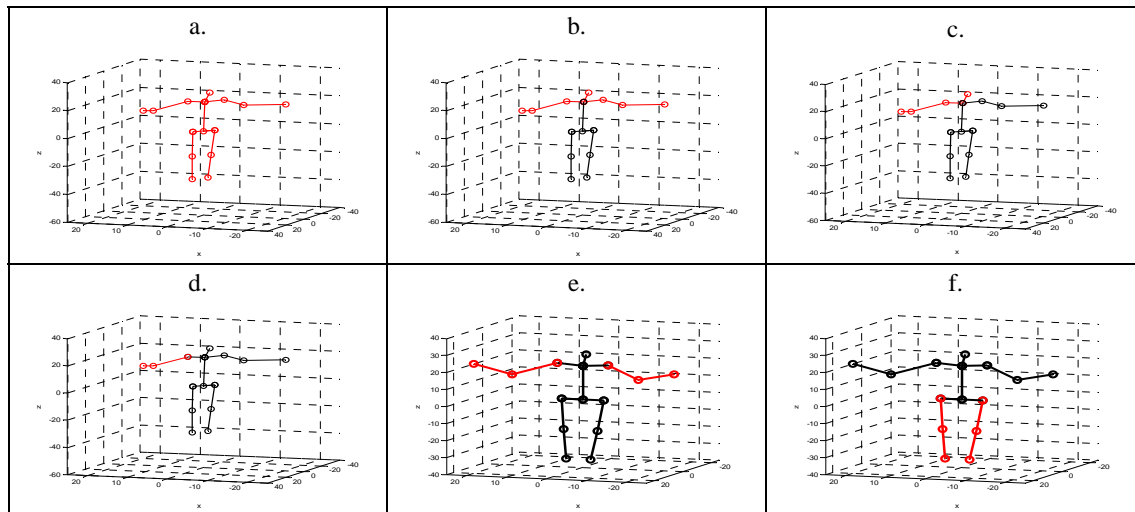


Figure-1. a. Full body. b. Upper body. c. Head and right hand. d. Right hand. e. Right hand and left hand. f. Lower body.

b. Feature extraction

In order to provide a simplified emotion recognition system, entire dynamic features were considered as the magnitude vector of position, velocity, acceleration and jerk. Eight statistical measures were defined as features such as mean, maximum, minimum, median, standard deviation, energy, entropy and rms. To represent the aggregate motion of parts of the body, we assign a feature vector to each of the limbs group: full body group (fifteen joints; 448 features), upper body group (eight joints; 256 features), the head-right hand group (head, neck, shoulder, elbow, wrist; 160 features), right hand group (shoulder, elbow, wrist; 96 features), right-left hand group (six joint; 192 features) and lower body group (six joint; 192 features). Figure-1 is shown the body part group considered in this study.

c. Classification techniques

Various types of body or hand features have been explored in research field, but there is no clear senses as to which joint are most informative. In response, we compared the system's recognition accuracy using five different classifier such as support vector machine (SVM) and naïve bayes (NB). The entire data in both testing and training sets are normalized in the range [0, 1]. The ability of the statistical feature set was identified by averaging ten times through subject dependent with selection 90% data for training and 10% data for testing.

3. RESULT AND DISCUSSIONS

The contribution of general features of gross body movements to the attribution of emotions was evaluated. The result is shown in Table-1 with averaging

four different emotions such as angry, happy, neutral and sad \pm standard deviation (std.). Analysis showed that the contribution of the full body and right hand components to perceive expressiveness revealed that for all emotions in action such as knocking, throwing, lifting and walking. Right hand body played a major role in discriminating between different emotions (anger, happy, neutral and sad) in knocking, throwing and lifting by higher voting of classification rate. While, full body is seen important to discriminate emotion in walking action.

We did not want to inadvertently restrict the motions to parts of the body. For example, if we based our experiments on knocking, we might bias the upper body to display most of the emotion. Furthermore, because several related studies have already performed systematic comparisons between similar motions, we wanted to investigate how their findings compared to our varied motion set. In this study, implementation of classifier to evaluate which joint are important in discriminate emotion of human action was success identified by higher accuracy rate.

From the result, we identify the recognition of full body expression is substantially harder, because the configuration of the human body has more degrees of freedom and its overall shape varies strongly during articulated motion. Thus, in this case such as knocking, throwing and lifting, considering high degrees of freedom may bring interference to emotion recognition, especially when involve with real situation. Therefore, considering right arm movement is informative enough as a controlled variable to classify emotion in these actions. While, in the cases of walking, we identify selection lower body does not giving a very good classification rate compare to upper body part to discriminate emotion. Thus, considering full



body in walking is seen good since this action involve entire joint movement. However, high number of dimensional data maybe influences complexity of

performance. Thus to solve **this problem**, another feature dimensionality reduction approach such as feature selection and reduction needed to deal with this problem.

Table-1. Entire averaging accuracy (%) \pm std. result of human emotion recognition using PNN and SVM classifier.

Action	Classifier	Full body (448 feature)	Upper body (256 feature)	Head+Rhand (160 feature)	Rhand (96 feature)	Rhand-Lhand (192 feature)	Lower body (192 feature)
Knocking	KNN	91.25 \pm 3.75	86.25 \pm 3.75	87.92 \pm 1.81	89.25 \pm 2.37	85.08 \pm 4.82	76.67 \pm 4.12
	FKNN	89.67 \pm 3.17	86.67 \pm 2.29	88.75 \pm 3.00	87.08 \pm 2.09	86.42 \pm 1.18	77.75 \pm 2.42
	PNN	27.50 \pm 1.30	46.58 \pm 1.73	67.08 \pm 1.19	81.67 \pm 2.19	59.92 \pm 2.40	56.92 \pm 3.29
	SVM	30.75 \pm 1.64	30.50 \pm 0.98	35.00 \pm 1.36	56.92 \pm 3.17	34.58 \pm 1.37	39.75 \pm 2.64
	NB	49.33 \pm 2.51	52.00 \pm 2.09	52.75 \pm 4.05	52.92 \pm 4.25	51.00 \pm 2.28	42.33 \pm 3.21
Throwing	KNN	87.90 \pm 1.74	88.07 \pm 2.93	86.13 \pm 2.57	87.56 \pm 2.27	87.56 \pm 3.21	75.71 \pm 3.40
	FKNN	89.75 \pm 2.53	86.47 \pm 2.36	85.80 \pm 1.92	85.88 \pm 2.20	86.97 \pm 3.95	75.80 \pm 2.91
	PNN	28.15 \pm 1.20	56.39 \pm 3.91	75.38 \pm 2.91	86.64 \pm 2.29	69.92 \pm 3.04	63.19 \pm 3.58
	SVM	31.93 \pm 1.86	35.63 \pm 1.69	46.97 \pm 4.16	58.82 \pm 2.41	42.27 \pm 1.98	37.06 \pm 1.22
	NB	49.66 \pm 3.53	51.01 \pm 3.50	53.61 \pm 3.75	53.87 \pm 2.22	50.34 \pm 2.26	44.03 \pm 3.17
Lifting	KNN	94.30 \pm 2.42	93.86 \pm 1.43	92.89 \pm 1.78	93.68 \pm 1.64	92.11 \pm 1.94	79.30 \pm 2.45
	FKNN	93.86 \pm 2.45	92.89 \pm 1.68	93.25 \pm 2.68	91.75 \pm 1.44	92.98 \pm 3.28	76.58 \pm 3.12
	PNN	55.88 \pm 5.00	82.11 \pm 2.81	88.07 \pm 2.03	91.32 \pm 2.13	87.37 \pm 2.20	73.07 \pm 3.31
	SVM	34.91 \pm 2.54	48.42 \pm 2.74	58.95 \pm 3.28	70.70 \pm 2.16	55.61 \pm 3.29	48.60 \pm 2.99
	NB	53.68 \pm 3.35	52.46 \pm 1.84	52.02 \pm 3.12	53.68 \pm 3.12	51.49 \pm 1.99	44.47 \pm 3.34
Walking	KNN	74.98 \pm 1.69	72.62 \pm 2.13	69.35 \pm 1.84	65.22 \pm 1.65	72.12 \pm 1.46	66.11 \pm 2.05
	FKNN	75.73 \pm 1.51	73.33 \pm 1.38	67.68 \pm 1.94	66.63 \pm 1.69	72.12 \pm 1.15	66.47 \pm 1.80
	PNN	37.64 \pm 0.69	51.79 \pm 2.00	62.02 \pm 1.68	64.90 \pm 2.02	61.01 \pm 1.56	60.06 \pm 1.46
	SVM	29.64 \pm 0.14	35.00 \pm 0.39	37.64 \pm 0.75	51.92 \pm 1.60	35.75 \pm 0.54	30.40 \pm 0.35
	NB	50.71 \pm 1.74	47.56 \pm 1.60	44.15 \pm 1.75	43.51 \pm 0.79	47.14 \pm 1.74	49.92 \pm 1.59

Another, one possible explanation for this low recognition rate of emotion, maybe due to the influence of the number of subjects. However, there are also possibilities that subject itself difficult to express some emotion such as happy and neutral in those actions [8]. Moreover, increasing number of unwanted joint also can influence performance of classifier. By breaking the high-dimensional search problem of body pose, the complexity is reduced considerably to achieve real-time performance. However, we do not refuse that the accuracy rate maybe influence by classification approach itself. For example, PNN and SVM are very sensitive with high number of redundancy feature. Therefore it gives low result in full body. KNN and FKNN in another hand influence by number of feature and less sensitive in redundancy feature.

4. CONCLUSIONS

Emotion may affect some or all of these motion control systems. In machine learning, the other factor

contributes to the accuracy of recognition are number of informative feature and data redundancy. Many features involved may contribute to the high accuracy of recognition and time constraint. Moreover, considering the whole body may become a disturbance to the system designed, especially when in involving more degrees of freedom. To clarify this point, considering the right arm movement is informative enough as a controlled variable to classify emotion in different activities such as knocking, lifting and throwing. However, there might be governed by the general rules of feature integration in the system which that the efficiency of the features might be determined first. This is important to avoid overlap between stimulus components and the receptive fields of different. Therefore, in the future more classification schemes and better model selection will be explored. Better cue fusions will also be studied.



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