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Estimating Mood Variation from MPF of EMG during Walking

Yuta Kinase and Gentiane Venture

Abstract— **The information on the mood included in behavior is classified into nonverbal information, and is included in behavior without necessarily being based on the intention of an agent. Consequently, it is considered that we can estimate the mood from the measurement of the behavior. In this work, we estimate the mood from the surface electromyogram (EMG) information of the muscles of the upper limb during walking. Identification of emotion and mood using EMG information has been done with a variety of methods until now. In addition, it is known that human walking includes information that is specific to the individual and be affected by mood. Therefore, it is thought that the EMG analysis of walking is effective in the identification of human mood. In this work, we made a subject walk in the various mood states and answer psychological tests that measure the mood. We use two types of tasks (music listening and numerical calculation) for evoking different moods. Statistical features of EMG signals are calculated using Fast Fourier Transform (FFT) and Principal Component Analysis (PCA). These statistical features are related with psychological test scores, using regression analysis. In this paper, we have shown the statistical significance of the linear model to predict the variation of mood based on the information on the variation in MPF of EMG data of the muscles of the upper limb during walking with different moods. This shows the validity of such a mapping. However, since the interpretability of the model is still low, it cannot be said that the model is able to accurately represent the mood variation. Creating a model with high accuracy is a key issue in the future.**

I. Introduction

In recent years, there has been an increasing demand for robotic systems closely related to human beings in areas such as security, daily life support and nursing in order to provide services that are tailored to individual and environmental information. In such a human–robot interaction, it can become a very effective capability that a robot can understand the mood of human when selecting a robot's action according to a situation. Rather than reacting in the same way for everyone at every time, if robots can take suitable action according to the mood of the human, we will be able to receive a better quality service.

Identification and use of human mood are important factors for various areas such as commerce, education, medical treatment, and many researches have been done so far as reviewed in [1]. The changes in autonomic nervous system (ANS) in activities that accompanies moods influence physiological data acquisition. Moods show a variety of physiological manifestations that can be measured with a diverse array of techniques. The physiological activities such as brain waves, skin responses, heart responses and muscle responses, reflect change of a mental condition. The information on the mood included in behavior is classified into nonverbal information, and is also included in behavior without necessarily being based on the intention of an agent [2]. Therefore, by measuring the parameters during the behavior, we can estimate the mood that is included in the behavior, and it may also be possible to generate parameters of the behavior from the degree of mood. Based on these techniques, the robot motion generation and human interface system are expected to improve.

In this work, we estimate the mood from the surface electromyogram (EMG) information of the muscles of the upper limb during walking so that we can estimate the mood from the behavior. Identification of emotion and mood using EMG information has been done with a variety of methods until now [3] [4] [5] [6]. Most are based on use of facial muscles. Walking is one of the key actions when identifying the information on humans. It is known that human walking includes information that is specific to the individual and be affected by mood [7] [8] [9]. That is, it is thought that the EMG analysis of walking is effective in the identification of human mood. In this work, we made a subject walk in various mood states and answer psychological tests that measure the mood. We use two types of tasks (music listening and numerical calculation) for evoking different moods. Statistical features of EMG signals are calculated using Fast Fourier Transform and Principal Component Analysis. These statistical features are related with psychological test scores [10], using regression analysis.

II. Methods

A. Experiment Overview

The subjects are three healthy males, and all subjects signed informed consent forms. The experiment is carried out one by one in a quiet room in which room temperature and lighting are adjusted appropriately and which does not have visitors. Test duration is about one hour per subject (including the time required for mounting the devices to the subject).

The purpose of this experiment is the measurement of EMG data during walking in a variety of moods. Fig.1 shows the schematic of the experimental environment, and Fig.2 shows snapshot of the experiments. In the experiment, the subjects perform two types of tasks (music listening and numerical calculation). The tasks are performed on two laptop computers. Moreover, the tasks are done by turns at two distant spaces in the room, and the subjects walk back and forth between them. After completion of each task, the subjects fill in questionnaires about their mood at that time, and then the subjects walk to the other space. The subjects repeat that work. In addition, the subjects were instructed to swing their arms naturally while walking in advance so as not

Department of Mechanical Systems Engineering, Tokyo University of Agriculture and Technology, 50012643019@st.tuat.ac.jp.

to fold their arms and put their hands in their pockets. At that time, the measurer measures EMG data of the subject during walking. Appearance of the measurer is not visible from the subjects because it is hidden using a partition. All instructions are transmitted to the subjects through the personal computer that is remotely controlled and after the explanations and the setting of the sensors no further interaction is possible between the staff and the subjects. After mounting of the device to the subjects, all the work is done only by the subjects during the experiment; the subjects are not disturbed by anyone during the experiment.

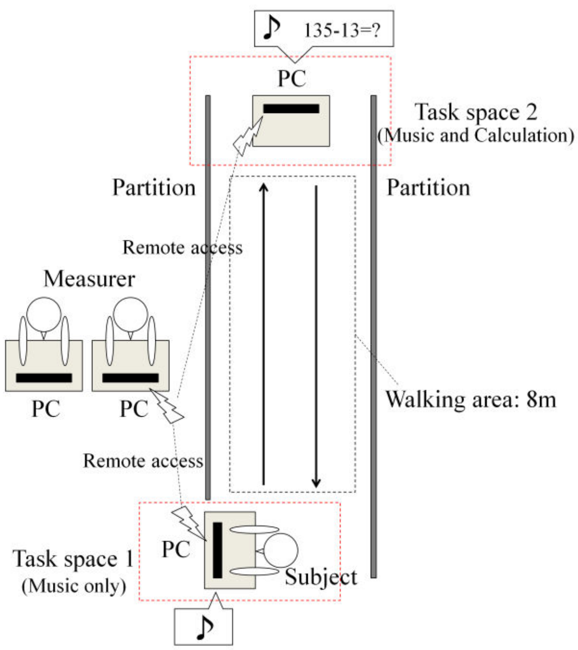

Figure 1. Schematic view of the experimental environment. The subject and the technical staff cannot interact once the experiment has started. The technical staff has a remote access to the subject PC's to monitor the experiments.

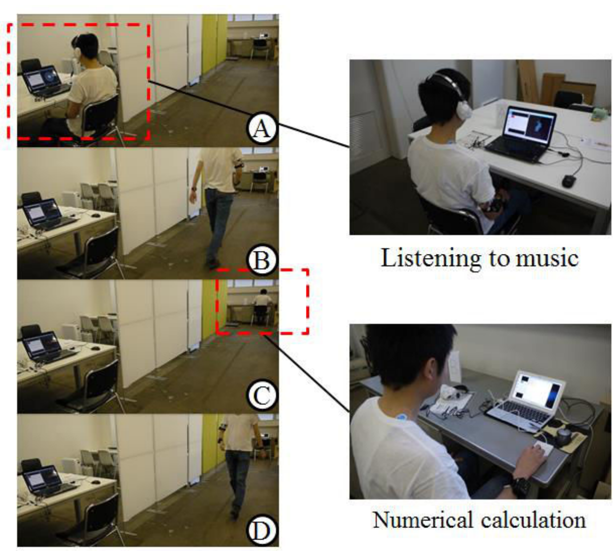

Figure 2. Snapshot of the experiments. (A) The subject is doing the task (in this case, task is listening to music) in the task space 1. (B) The subject is moving to the task space 2 from the task space 1. (C) The subject is doing the task (in this case, task is numerical calculation) in the task space 2. (D) The subject is moving to the task space 1 from the task space 2.

B. EMG Data Acquisition

EMG is an electric signal which occurs at that time of muscle contraction [11]. In this work, the EMG signals are recorded using myon 320 (Myon Inc.) and BlueSensor N Ag/AgCl disposable surface electrodes (Ambu Inc.). myon 320 system contains wireless transmission system, so that activities of the subjects are not interfere with by the device. The EMG signals are amplified (gain 1000), band-pass filtered between 5 Hz and 500 Hz and sampled at 4000 Hz. The electrodes are positioned over each muscle belly along the muscle fiber direction. The inter-electrode distance in each pair of EMG electrodes is 20mm. The skin is rubbed with cotton containing alcohol to minimize the impedance. In order to prevent contamination of the signal, the cables of the sensor are fixed to the subject's body using the surgical tape. The electrodes were attached to the skin over four muscles: biceps, triceps, middle deltoids, and upper trapezius of the right-hand side upper limb. It is confirmed that there is a clear pattern of emotion-specific posture features such as a head angle and an elbow angle while walking [7]. Therefore, we think that the upper limb is a part of the body to express the mood well while walking.

C. Psychological Test

In this work, we use two-dimensional Mood Scale (TDMS) proposed by Sakairi et al. as a psychological test for scoring the mood of the subject. In [10], they validated the TDMS test reliability on 220 subjects. TDMS consists of eight questions on a 6-point scale, and can quantify the state of mind at the time of measurement. The result of TDMS is expressed as a score of "pleasure" and "arousal" (from -20 to 20). In other words, high pleasure indicates a comfortable and positive state, high arousal indicates an excited and active state (Fig. 3). Since TDMS is based on the two-dimensional model of a state of mind, it can measure both a negative state and a positive state. Moreover, since it can be carried out in a short time (less than 1 minute), it is suitable for temporal observation of state of mind changes.

D. Task to Evoke Mood

In this work, two types of tasks have been used for evoking a variety of moods of the subjects. One of the tasks is listening to music. In the selection of music, we have referred to the affective value list of musical pieces created using the affective value scale of music (AVSM) and multiple mood scale (MMS) [12], and we have used the music with a high, middle and low uplift score in that list for our experiment. In addition, all pieces of music have been adjusted to a duration of about three minutes. The subject opens the music file in a personal computer, and listens to music using headphone. TABLE I shows the music used in the experiment.

The other task is a numerical calculation. We have prepared two continuous subtractions as monotonous and troublesome work. One is subtracting 13 from 600 and the other is subtracting 13 from 200. The calculation is performed on a personal computer using the program written in C. The subject can end calculation, when it becomes impossible to subtract more (success). However, when they are mistaken in calculation on the way, they are made to redo from the beginning compulsorily. Moreover, when calculation does not finish within the time limit (three minutes), it is ended compulsorily (failure). After the time limit, the message to a subject is displayed on the display of a personal computer, and the contents changes with success or failure. It is expected that numerical calculation evokes either a more aggressive or frustrated mood upon failure, or self-satisfaction when successful, than listening to music. Fig.4 shows the stimulus protocol of our experiment. In one space of the two, the task which is listening to calm music is always given to the subject. The other space gives the subject the task which is listening to music (uplifting and depressive) and the numerical calculation. By always putting the task of listening to calm music between other tasks, we try to change the subject's mood around a certain standard in the experiment.

E. Feature Extraction and Regression Model

In this work, a regression-based model is created to estimate linearly the subjects' TDMS "pleasure" score based on EMG data. The regression line is calculated to minimize the sum of squared errors which is the difference of the actual pleasure score and the estimated pleasure score. Key information are extracted to be used to create regression model from the EMG data using Principal Component Analysis (PCA). EMG includes several information such as time, amplitude and frequency. In this work, we use the mean power frequency (MPF) obtained by Fast Fourier Transform (FFT) of the EMG data for PCA. First, FFT is performed on each of the EMG data for three seconds which is located near the center of each data, and MPF is calculated for each muscle. MPF can be calculated as follows:

$$MPF = \int_0^\infty fP(f)df \Big/ \int_0^\infty P(f)df$$

Where: P is power, f is frequency.

Next, in order to obtain the amount of variation in MPF, the difference between each MPF and the previous one is calculated. Then, PCA is performed for each frequency range using all the subjects' data (21 pieces) about MPF variation of all the muscles. Finally, principal component scores of all the principle components whose eigenvalue is equal to or greater than 1 is calculated about all each trial. The principle component whose eigenvalue is equal to or greater than 1 means it is summarized information which has one or more factors' information.

In regression model creation, multiple linear regression analysis (MRA) was performed using all the subjects' principal component score as an explanatory variable and the amount of variation in TDMS pleasure score which is the difference between each pleasure score and the previous one as a response variable. By considering the score not using an absolute value but using a relative value, we can take into consideration the individual difference of the reaction to a stimulus. In addition, we chose the variable using stepwise method in MRA. PCA and MRA were carried out in the Excel Statistics 2012 environment.

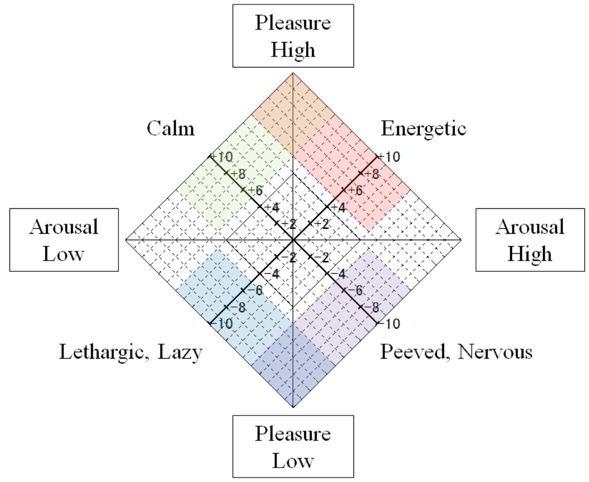

Figure 3. Two-dimensional graph of the state of mind

TABLE I. MUSIC USED IN THE EXPERIMENT

Type	Musical piece (composer)
Uplifting music	The Arrival of the Queen of Sheba (Handel)
Depressive music	Adagio in G minor (Albinoni)
Calm music	Music for the Royal Fireworks (Handel) Largo (Handel) La Traviata Prelude to the 1st act (Verdi) Winter mvt2 Largo (Vivaldi)

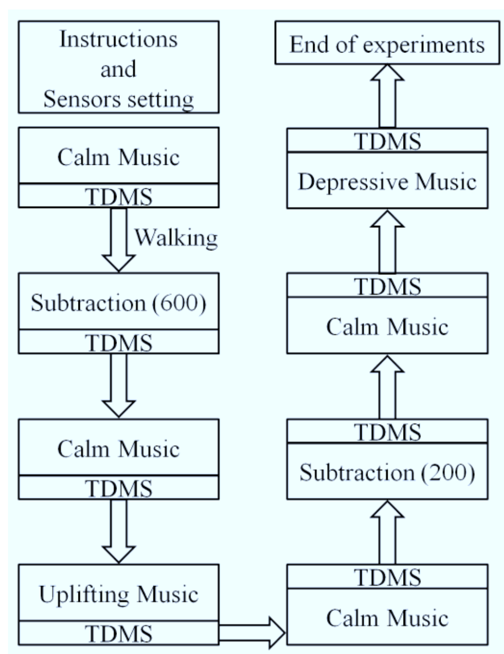

Figure 4. Stimulus Protocol. One subject performs eight tasks and walking.

TABLE I. REGRESSION ANALYSIS RESULT

Beta	R Square	Adjusted R Square	Standard error	P-value
0.725	0.526	0.501	3.79	< 0.001

*Model: 1st principal component score of the frequency range from 5 to 50 Hz - pleasure score variation.

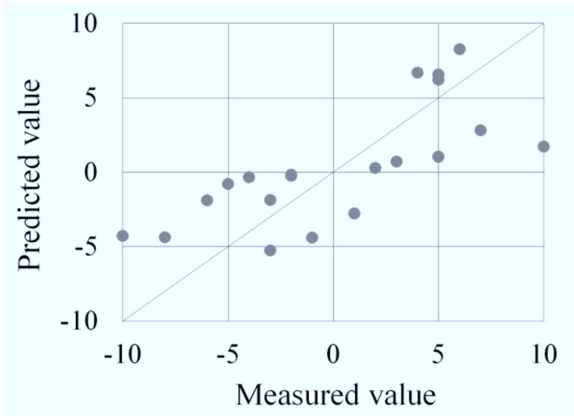

Figure 5. Measured Value – Predicted Value of pleasure score variation

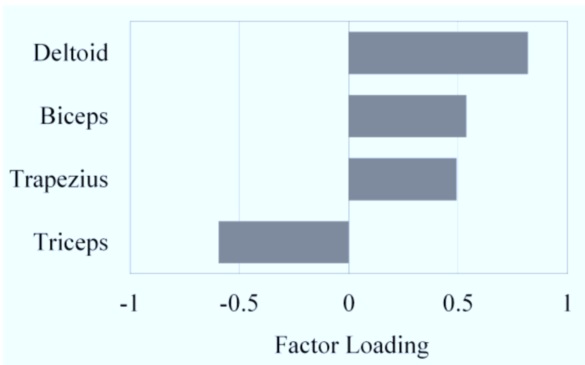

Figure 6. Factor Loadings

III. RESULTS

As a result of the regression analysis, we have confirmed a statistically significant positive correlation of the model whose explanatory variable is the 1st principal component score of the frequency range from 5 to 50 Hz ($p < 0.001$). TABLE II shows the results of the regression analysis. Adjusted R Square means how much an explanatory variable can explain the variance of a response variable; it expresses the interpretability of a model. This model can explain about 50% of the amount of the variation in pleasure score. Fig.5 shows the predicted values from this model and the measured value of the amount of the variation in pleasure score. This figure also shows that pleasure score used in the analysis can be measured without bias. Interpretability of the model is low. For example, the work on the emotion recognition at the time of the gait using the motion capture system by Venture et al. shows a total average recognition rate of 69% about four emotions (joy, anger, sadness and neutral) [8]. Moreover, the work on the emotion recognition using EMG of the face muscles by Gruebler et al. achieves 90% correct recognition of smile [6]. Our work also wants to aim at the recognition rate beyond these. In the frequency range from 5 to 50 Hz, the principal component used for the model has the information that the eigenvalue is 1.556 and the contribution ratio is 38.9%. Fig.6 shows the factor loadings of the principal component. This figure shows this principal component contains the information of all the muscles almost equally. It is considered that the factor loading of a deltoid is large because deltoid is a muscle that is related to the movement of shoulder abduction which are major operation in the swing arm. In this paper, we did not confirm a significant correlation of the model whose response variable is "arousal" scores. When creating the arousal score model, we think that it is necessary to collect more data and use the EMG data which performed different processing for the explanatory variable.

IV. CONCLUSIONS AND FUTURE WORKS

In this paper, we have shown the statistical significance of the linear model to predict the variation of mood based on the information on the variation in MPF of EMG data of the muscles of the upper limb during walking with a variety of mood. This shows the validity of such a mapping. However, since the interpretability of the model is still low, it cannot be said that the model is able to accurately represent the mood variation. Creating a model with high accuracy is a key issue in the future. Therefore, it is necessary to collect more subjects' data and examine new explanatory variables. We need to try a variety of patterns about the part of muscle and the method of processing EMG data to find the element related to mood. Moreover, we are going to consider use of biological information other than EMG, such as electrodermal activity and joint viscoelasticity.

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