A Database of Japanese Emotional Signals Elicited by Real Experiences

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Abstract. This paper presents a Japanese emotional database that contains speech and physiological signals that can be used to develop algorithms for emotion recognition using audio, physiological signals, or several combined signals. Research on emotions was underpinned by using this database, and health-care oriented applications were the main reason this database was constructed. All six basic human emotions were elicited by using real emotional experiences, which had different impacts on health conditions. We also describe the experimental setup and protocols. Finally, signals from more than 50 people were included in the database.

Keywords: Emotion elicitation · Emotional experience recalling · Health-care oriented emotion database · Speech signals · Physiological signals

1 Introduction

Most developed countries in modern society are facing serious problems with the increasing number of lifestyle related diseases, which are greatly influenced by negative emotions and unstable emotional states. Siriois and Matthew demonstrated that negative emotions have deleterious effects on health in patients with coronary heart disease [1], while Hinchcliffe found that emotions are a precipitating factor in Menieres disease [2]. Moreover, other research [3] has found negative emotional experiences such as combat experiences have long-term effects on human health in later life.

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Although affective computing has been extensively studied due to developments in technologies related to human-machine interface applications, few databases have been constructed for health-care oriented research. Accurate systems of emotion recognition in daily life for health-care purposes are becoming an urgent research topic in contemporary society. Thus, this paper describes the design and implementation of a database that contains Japanese emotional signals elicited by real experiences with six basic human emotions of happiness, sadness, disgust, surprise, anger, and fear [4].

Emotion researchers have posed many arguments and had numerous discussions on real or acted emotions as research targets. Thus far, many well known databases have been targeting acted emotions such as the Berlin database [5] and much research has been done based on this database for applications of human machine interfaces. However, the literature has also indicated that there are indeed great differences between acted and real emotions, which prevent us from using them for health-care purposes. Three different findings are summarized below.

- Acted emotions have less or no effect on human health conditions, while real emotions have impact on health and may influence health for a long term in later life.
- Acted emotions are usually expressive and easily identified by others, while real emotions vary in terms of expressions due to individual differences.
- Other peoples assessments are usually adopted in the process of evaluating acted emotions; however, they are not accurate for identifying real emotions [6] and make the selected data unsuitable for developing algorithms of real emotions.

Our focus was on emotions that influence human health conditions, which are aroused by real emotional experiences. We relied on participants' self-assessments to evaluate performance during the experiments.

2 Procedure of Experiments

The experiments consisted of two parts, which were an online survey and onsite experiments. The Internet survey was designed to collect materials representing participants' real emotional experiences. After the materials for emotion elicitation were collected, the onsite experiments were arranged to collect the speech and physiological signals.

2.1 Online Survey

Basic information such as that on gender and age ranges was collected from an online survey. Simple questions to collect information on participants' real emotional experiences were asked in forms such as "Please explain one or two memories that aroused your deepest emotions of happiness".

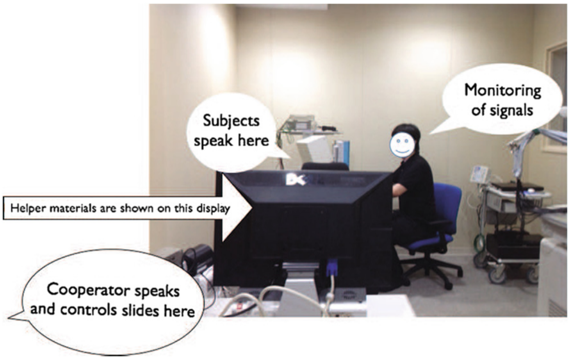

Fig. 1. Environment setting for experiment from viewpoint of coordinator

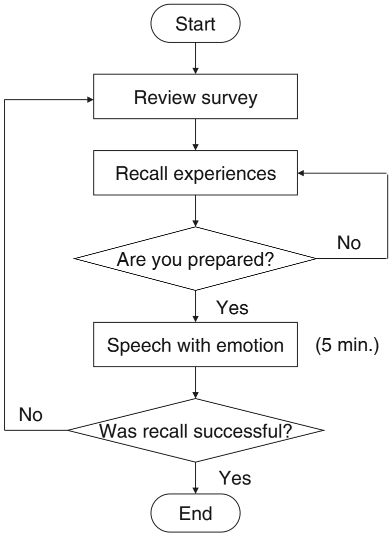

Fig. 2. Procedure for eliciting emotions by recalling experiences

2.2 Onsite Experiment

There is a photograph of the onsite environment setting for an experiment in Fig. 1. An assistant introduced the experimental protocols, how the sensors were worn, and checked the sensor signals for participants, while a coordinator helped to elicit their emotions.

The participants recalled their emotional experiences and described them during the experiment, and the coordinator asked them questions and made small talk about the same emotions with prior knowledge from the survey that they had previously completed. The procedure for eliciting the six emotions is outlined in Fig. 2.

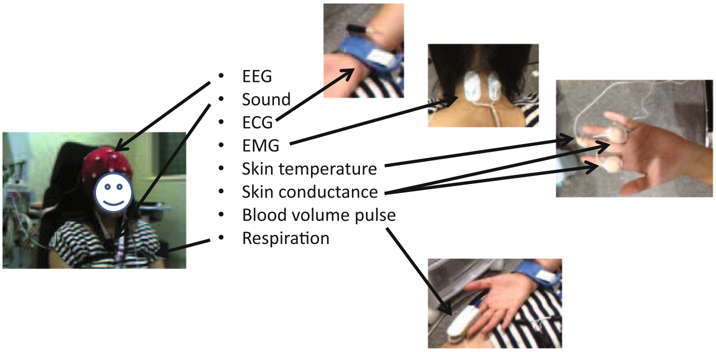

Fig. 3. Placement of sensors and signals that were collected

Eight signals were collected in the experiments including those from electroencephalography (EEG), speech, electrocardiography (ECG), electromyography (EMG) skin temperature, respiration, blood volume pulse, and skin conductance. Where the sensors were worn and what signals were collected are illustrated in the photographs in Fig. 3. Finally, the participants completed a five-point Likert scale for self-assessment.

2.3 Description of Signals

How signals were collected and explained in the following. Examples are also given.

Speech. Speech signals are very popular in emotion research since they are easy to obtain in daily life for making applications. Researches have been extensively conducted for extracting features from utterance (phrases, short sentences, etc) [7]. Some recent researches have been focusing on an issue that questions whether or not the utterance level is the right choice for modeling emotions [8]. Moreover, Valuable but neglected information could be utilized in the segment-level feature extraction approaches. This hypothesis is supported by many researchers [9], based on the fact that improvements can be made by adding segment-level features to the common utterance-level features. A latest perspective is to extract useful information from only short-time segments [10]. We collected long fragments of speech signals for the six emotions (Fig. 4) in this database.

EEG. EEG measures voltage fluctuations resulting from ionic current flows within the neurons of the brain. Much research [11] has revealed that there is a

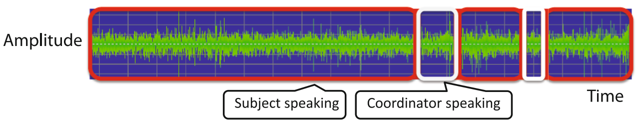

Fig. 4. Example of collected speech signals

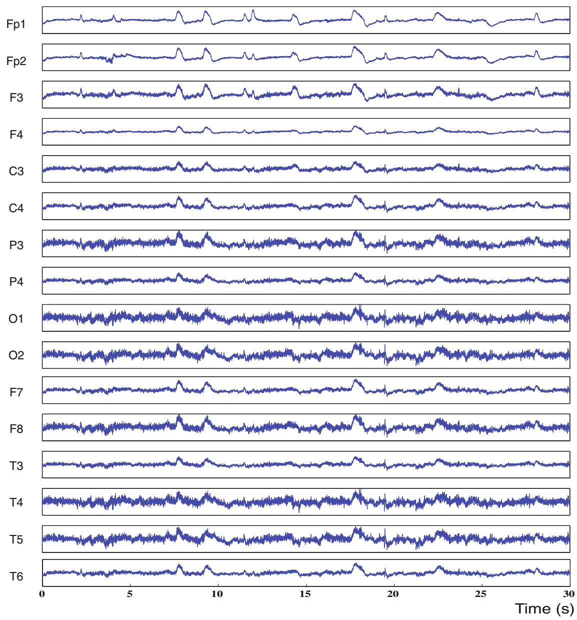

Fig. 5. Collected EEG signals

relationship between EEG signals and different kinds of emotions and it is advantageous to use these as it is difficult for people to manipulate EEG signals. It has been shown that a correlation exists between emotions and brain activity [12], especially in the prefrontal cortex and the amygdala [13]. By combining EEG and other physiological signals, Takahashi and Tsukaguchi achieved about 60 % accuracy for classifying pleasure and displeasure [14]. A latest research described a new group of features called cross-level wavelet features, which largely increased the performance of emotional valence recognition to more than 90 % accuracy [15]. Figure 5 illustrates the positions at which the EEG signals were collected according to 10-20 International system and provides examples of collected signals. The reference electrode was A1.

ECG. ECG is used to measure the electrical activities of the heart. QRS positions and other features have been reported to have a correlation to emotions [16]. ECG was also used with other signals such as speech for improving emotion recognition performance [17]. Figure 6 has an example ECG with QRS positions.

Respiration. Respiration signals record the activity of the lungs. Different respiration patterns also provide emotion information. It's usually used together with other physiological signals for emotion recognition [20]. A respiration signal was recorded with a belt-type sensor, as shown in Fig. 7.

EMG. EMG is a technique for evaluating and recording the electrical activity produced by skeletal muscles. Research has indicated the frequency of muscle

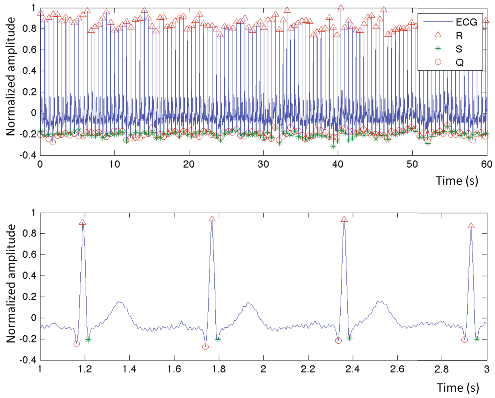

Fig. 6. ECG signal with QRS positions

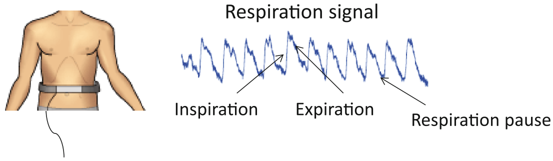

Fig. 7. Respiration signal (right) with sensor position (left)

tension, action potential amplitude, and the duration of action potential have a relationship with emotions [18].

Skin Temperature. The literature has indicated that skin temperature is dependent on the emotional state [19]. We measured skin temperature at the finger tips.

Blood Volume Pulse. Photoplethysmography (PPG) is used to bounce infrared light against the skin surface and measure the amount of reflected light. The literature has indicated that high values for blood volume pulse represent anger and stress, while low values represent happiness and relaxation [20]. The signal from a blood volume pulse from a finger tip is given in Fig. 8.

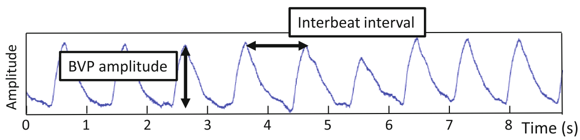

Fig. 8. Signal from blood volume pulse

3 Description of Data

Speech and physiological signals from fifty healthy Japanese participants were successfully collected. EEG and ECG signals were recorded by a Nihon kohden

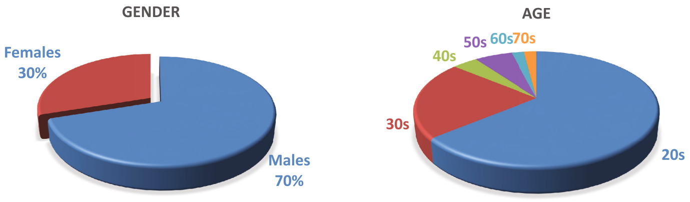

Fig. 9. Data distribution related to gender and age

EEG-1200 using electrodes placed according to the international 10-20 system; Other physiological signals were recorded using Bioplux. This experiment was conducted with the permission from Research Ethics and Safety committee of The University of Tokyo.

Figure 9 has pie charts of the age and gender distributions of participants in the experiments. Most of the participants were in their 20s and 30s and 70 % were male and 30 % were female.

A self-assessment survey was administered immediately after each experiment. The question of "Did you successfully arouse the emotion of happiness?" was asked after each emotion stimulation. Then, five levels of confidence could be selected as answers, where level 1 (L1) represented the lowest confidence level of a participant's assessment and level 5 (L5) represented the highest confidence level. Figures 10, 11, and 12 plot the answers from the participants.

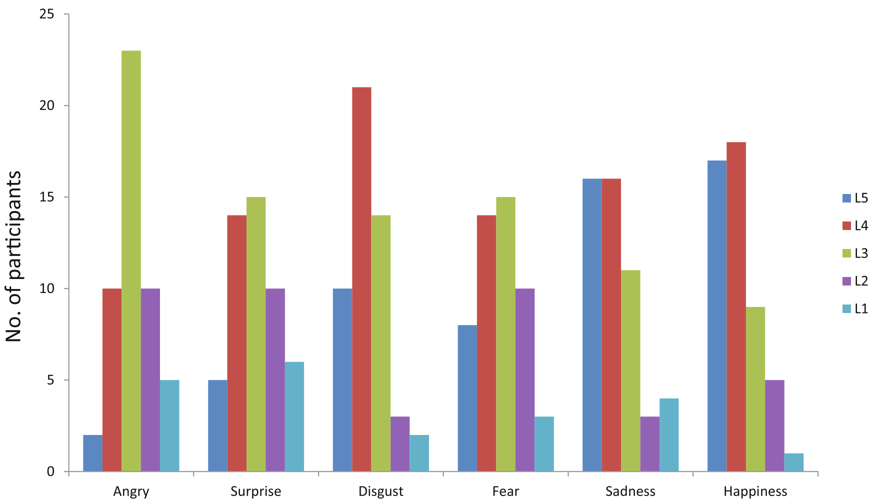

Fig. 10. Summary of self-assessments

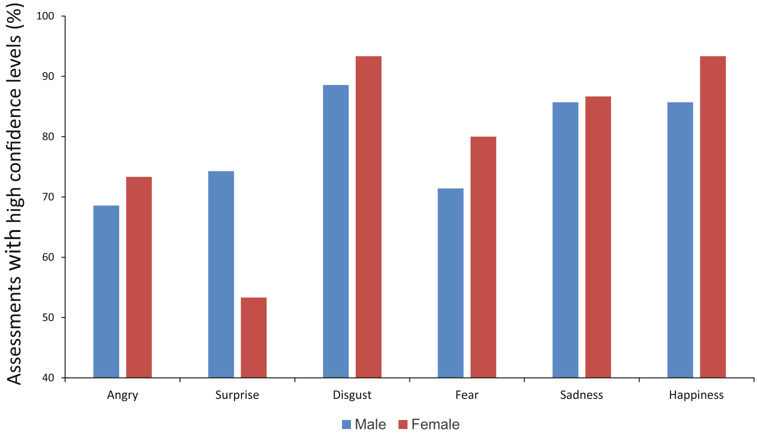

Fig. 11. Summary of self-assessment results according to gender. Data (y-axis) indicate percentage of confidence levels no less than three.

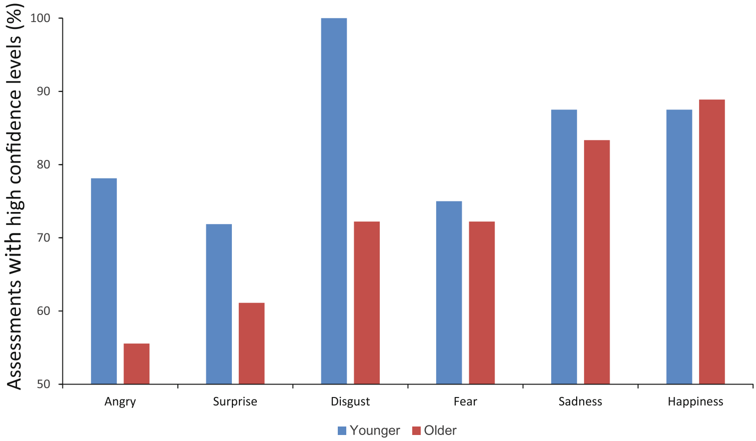

Fig. 12. Summary of self-assessment results according to two age groups of less and greater than 30. Data (y-axis) indicate percentage of confidence levels no less than three.

4 Discussion

We could easily see from the self-assessment result of Fig. 10 that the majority of participants (80 %) were confident emotions were elicited with a confidence level of not less than three. Japanese participants were more confident about their emotional arousal of happiness and sadness out of all six emotions, and very confident of their emotional arousal of fear and disgust. They found it relatively more difficult to reach the emotion of anger than the other emotions, and surprise was difficult to arouse during the experiments. In Fig. 11, female participants were generally more sensitive to emotions such as happiness, fear, disgust, and anger, while male participants were more confident of surprising experiences. Male participants were less confident about fear experiences than female participants as expected since males are usually stronger and more difficult to scare. However, it seems that male participants were more confident of surprising experiences. This seems difficult to understand at first glance, but it might be due to careful preparations of surprising scenarios arranged by their families. A fact supporting this hypothesis was that most surprising situations were arranged by females based on our survey. Another phenomenon was that more female participants were confident of their anger experiences than male participants. This could have been caused by fewer ways for them to release their emotion of anger compared to male participants. We divided the participants into two groups of different ages with ages younger and older than 30. We found that younger people had more confidence about the majority of emotions according to statistical analysis (Fig. 12), especially stronger emotions such as disgust, anger, and surprise. However, older participants retained more happy experiences and had lower confidence with strong negative emotions and surprising experiences.

5 Conclusions and Future Work

We introduced a Japanese database with signals involving six basic human emotions elicited by real experiences to develop an algorithm for health-care oriented applications. Speech signals and a variety of physiological signals were included in the database. Since other people's assessments create errors in real emotion targets, we only carried out self-assessments and analyzed the results.

Self-assessments are very reliable for labeling data on real emotions. Remaining issues may be related to methods of assessment, other than subjective methods of evaluation such as self-assessments, and further objective methods of evaluation should be proposed to obtain a more reliable database.

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