Judging Emotion from EEGs Using SVM and EEG Features

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Abstract - *For a robot to converse naturally with a human, it must be able to accurately gauge the emotional state of the person. Techniques for estimating emotions of a person from facial expressions, intonation and speech content have been proposed. This paper presents a technique for judging the emotion of a person using EEGs. Accuracy of emotion judgment using EEG features of all subjects was 43.6% and using EEG features of only principal subject was 55.7%. However, performance accuracy remains low, and continued development is required through further development of methods for both reducing noise mixed in with EEGs.*

Keywords: EEG, judging emotion, SVM

1 Introduction

For a robot to converse naturally with a human, it must be able to accurately gauge the emotional state of the person. Techniques for estimating emotions of a person from facial expressions, intonation and speech content have been proposed. This paper presents a technique for judging the emotion of a person using EEGs, differing from the data used to date.

2 Overview of Proposed Technique

The objective of this technique was to read the emotions of a conversation partner from EEGs.

EEGs acquired from the subject are used as source EEGs. Emotions of the subject at that time are acquired simultaneously. Spectrum analysis of the source EEGs to which emotion flags have been assigned is performed every 1.28 s, and the EEG features of θ waves (4.0 Hz to 8.0 Hz), α waves (8.0 Hz to 13.0 Hz) and β waves (13.0 Hz to 30.0 Hz) are determined (Fig 1).

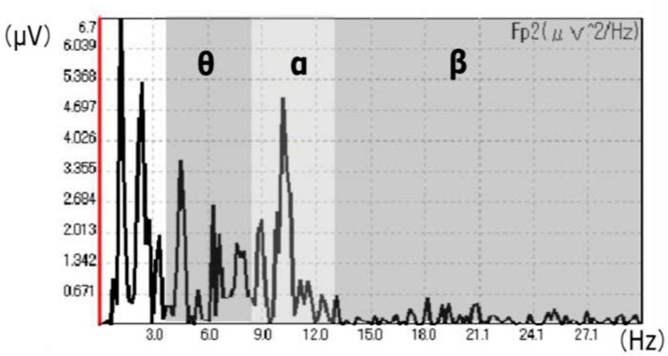

Fig.1 Spectrum analysis of the source EEGs

Emotion are judged from EEGs by support vector machine (SVM) [1] using the learning data which is EEG features to which emotion flags have been assigned was determined in this study. Emotions judged in this study were pleasure, anger, sadness, and no emotion.

3 Acquisition of Source EEGs and Emotions

EEGs were measured at 14 locations, at positions conforming to the International 10-20 system (Fig.2) [2]. Subjects fitted with an electroencephalography [3] cap were asked to watch a Japanese film for approximately 2 h while trying to gauge the emotions of the speakers in the film, and source EEGs were acquired. Images were frozen for each of the 315 speakers in the film, and the subject was asked what emotion the speaker was feeling at that time.

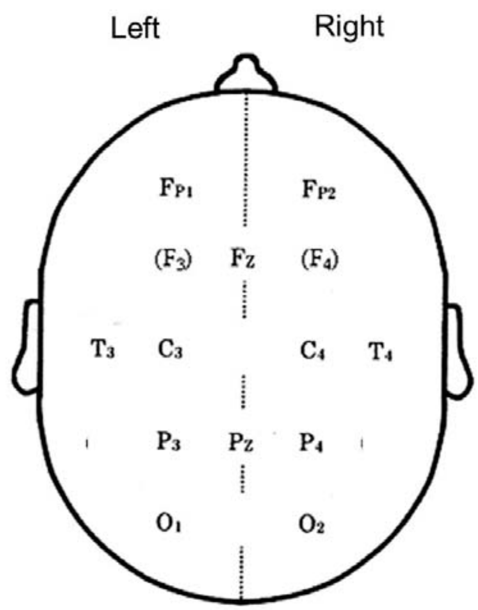

Fig2. 14 locations to measure EEG conforming to the International 10-20 system

Eighteen subjects were used, and viewing was divided into four sessions to reduce the physical burden on subjects. Before and after the film, EEGs corresponding to open-eye and closed-eye states were measured for approximately 1 min each, and these data were used when normalizing EEG features.

4 Normalization of EEG Features

EEGs show changes in voltage intensity over time within an individual, and base voltage intensity differs among individuals. For this reason, the possibility of misjudgment exists because those values differ greatly even among EEGs with similar waveforms. To solve this problem, linear normalization and non-linear normalization were performed.

4.1 Linear Normalization

This was performed to take into account how EEGs vary over time depending on the subject. Since the eyes were open while viewing the film, linear normalization was performed based on EEG features from the eyes-open state, acquired both before and after the experiment.

EEG feature $Linear\_al_{ij}$, obtained by linear normalization of first EEG feature al_{ij} at a certain point in time during the experiment, is expressed by Formula 4.1:

$$Linear\_al_{ij} = al_{ij} + \left\{ \left(\frac{q_1 - q_2}{p_2 - p_1} \times l + q_2 \right) - \left(\frac{q_2 - q_1}{p_2 - p_1} \times l + q_2 \right) \right\} / 2 \tag{4.1}$$

4.2 Non-linear Normalization

This was performed to take into account the differences in base voltage intensity among individuals.

Non-linear normalized values were determined using Formula 4.2, where $f(x)$ is the EEG feature after non-linear normalization has been applied, x is the EEG feature applied in non-linear normalization, x_{min} is the minimum EEG feature of the individual, and x_{max} is the maximum of the same data. As a result, EEG features with large values are compressed and EEG features with small values are expanded. The degree of intensity of voltage of an individual's EEGs can thus be accounted for.

$$f(x) = \frac{\log(x - x_{\min})}{\log(x_{\max} - x_{\min})} \tag{4.2}$$

5 Evaluation Experiment

5.1 Experimental Method

The following two kinds of evaluations were done. The method of the first kind used was a leave-one-out cross-validation, a technique in which one data point from all test data was extracted and compared with all the remaining data.

This study used 2887 EEG features obtained by excluding outliers from the total of 5670 EEG features. The emotions of the 2887 EEG features used in this study comprised 541 anger features, 726 sadness features, 1226 no-emotion features, and 394 pleasure features.

The method of the second kind is a method of using the EEG features only of the principal subject for the learning data of SVM when leave-one-out cross-validation is done.

5.2 Evaluation of Accuracy

Figure 3 shows the result of the emotion judgement from EEGs. Accuracy of emotion judgment from EEGs using EEG features of all subjects was 43.6% and using EEG features of only principal subject was 55.7%. As a comparison, the result of doing the emotion judgment at random is accuracy of 25.0%. The method proposed herein thus appears valid.

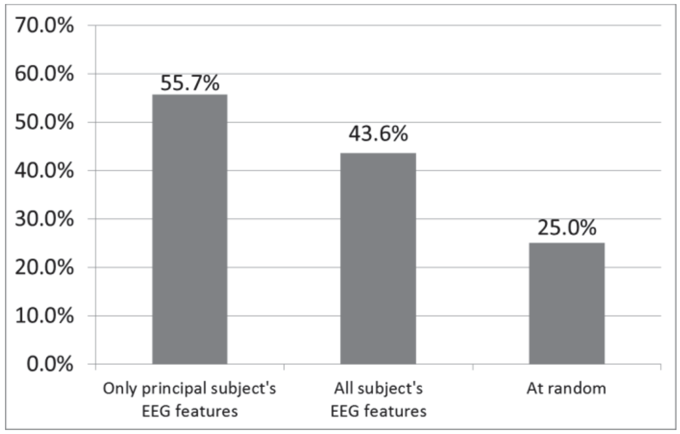

Fig.3 result of the emotion judgement from EEGs

However, performance accuracy remains low, and continued development is required through further development of methods for both reducing noise mixed in with EEGs.

6 Conclusion

We have presented a technique for gauging the emotions felt by a person from EEGs. Accuracy of emotion judgment using EEG features of all subjects was 43.6% and using EEG features of only principal subject was 55.7%. It can be said that a personal adaptation is very effective as the results. However, performance accuracy remains low, and continued development is required through further development of methods for both reducing noise mixed in with EEGs.

We plan to continue research aimed at improving the accuracy of emotion judgment by EEGs in the hopes of developing robotic systems that can participate in conversation and activities while gauging human emotional states.

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