Emotion Judgment Method Using a Clustered EEG Feature Knowledge Base

Seiji Tsuchiya¹, Mayo Morimoto², Misako Imono¹ and Hirokazu Watabe¹

1. Dept. of Intelligent Information Engineering and Science, Faculty of Science and Engineering, Doshisha University, Kyo-Tanabe, Kyoto, 610-0321, Japan

2. Dept. of Information and Computer Science, Graduate School of Engineering, Doshisha University, Kyo-Tanabe, Kyoto, 610-0321, Japan

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, differing from the data used to date. Accuracy of emotion judgment was 33.0%, which is still low, but we believe we obtained sufficient clues that will lead to improved accuracy, such as the validity of knowledge base clustering.

Keywords: EEG, judging emotion, clustered knowledge base.

1. Introduction

Authors are conducting research aiming to develop new interfaces that follow the mechanism of human communication, focusing on human common sense [1-8]. Humans, in such communication, are able to appropriately interpret ambiguous information that they receive and carry on a smooth conversation. Common sense is knowledge (ability) that only man has. The person can express feeling either sense of incompatibility or unnatural by using common sense. Moreover, the person can appropriately interpret when the sense of incompatibility and unnatural are felt.

Especially, authors focus on the emotion of which common sense and attempt to compose a method that judge the user's emotion, based on EEGs. 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. Fig. 1 shows outline of the proposed technique of emotion judgment 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. 2). A knowledge base of EEG feature is created by clustering the determined EEG features.

To judge emotion from EEGs, the distance between EEG features of the EEG to be judged and the data in the EEG feature knowledge base to which emotion flags have been assigned was determined in this study, and emotions were then judged. Emotions judged in

Corresponding author: Seiji Tsuchiya, Ph.D., associate professor, research fields: knowledge processing, concept processing and semantic interpretation. E-mail: stsuchiya@mail.doshisha.ac.jp.

Fig. 1 Outline of emotion judgment from EEG.

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. 3) [9]. Subjects fitted with an electroencephalography [10] 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.

Sixteen 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 Eq. (1):

$$Linear_al_{ij} = al_{ij} + \left\{ \left(\frac{q_1 - q_2}{p_2 - p_1} \times l + q_2 \right) - \left(\frac{q_2 - q_1}{p_2 - p_1} \times l + q_2 \right) \right\} / 2 \quad (1)$$

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 Eq.(2), where $f(x)$ is the EEG feature after non-linear normalization has been applied, x is the

Fig. 2 Spectrum analysis of the source EEGs.

Fig. 3 14 locations to measure EEG conforming to the International 10-20 system.

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.

$$f(x) = \frac{\log(x - x_{min})}{\log(x_{max} - x_{min})} \quad (2)$$

5. Clustering of EEG Feature Knowledge Base

As described in Section 3, a total of 315 EEG features from each of the 16 subjects were obtained, for a total of 5040 EEG features. If these numerous data points were used as a knowledge base, there would be concern about degradation of emotion judgment performance because of the large number of objects for comparison. Thus, if the EEG feature knowledge base that will serve as an object of comparison can be clustered and grouped based on specific emotions, the number of data points can be limited and performance degradation reduced.

The k-means method, which uses a threshold value, was employed as the clustering technique. The algorithm applied is shown below. In clustering, total

error between EEG features was defined as distance, using EEG features determined by compiling data from 14 locations and three frequencies, for a total of 42 elements, into one element. EEG features of compared EEGs A and B were taken as al and bl , respectively. When EEG features of the i^{th} frequency and j^{th} electrode of each EEG feature were taken as al_{ij} and bl_{ij} , respectively, $Distance(al_{ij}, bl_{ij})$ was expressed using Eq. (3). The distance of EEGs A and B overall, $All_Distance(A, B)$, was thus expressed using Eq. (4).

$$Distance(al_{ij}, bl_{ij}) = |al_{ij} - bl_{ij}| \quad (3)$$

$$All_Distance(al_{ij}, bl_{ij}) = |al_{ij} - bl_{ij}| \quad (4)$$

The clustering technique was as follows:

The number of clusters was set, and clusters are randomly assigned to each of EEG features $x_i (i = 1, \dots, n)$.

The centroid $V_j (j = 1, \dots, K)$ of each cluster is determined based on the assigned EEG feature. The centroid is the mean of the elements of the EEG feature in the cluster.

The distance between each x_i and each V_j is determined, and when the distance of the nearest centroid is equal to or less than the threshold value, x_i is assigned to that cluster.

The process is complete if the centroids of all x_i clusters have not changed in the above process. Otherwise, Steps 2 and 3 are repeated.

5.1 The Number of Clusters

When the number of clusters was set to a power of 2 between 1 and 2,048, accuracy was evaluated by clustering based on the various threshold values. As a result, the cluster number in the range of 32 to 128 at which the correct rate was maximized was used.

5.2 Threshold Value

In the k-means method, clusters to be partitioned into are set first, but sometimes the number of clusters

is less than the set number depending on the integration method. In such cases, the EEG knowledge base after clustering is smaller than the number of clusters initially set.

5.3 Determination of the Number Clusters and Threshold Value

Table 1 shows the results of the emotion judgment accuracy in the difference between the number of clusters and the threshold value.

The emotions of the 3436 EEG features used in this study comprised 1159 anger features, 575 sadness features, 1164 no-emotion features, and 538 pleasure features. In cases where the number of data points differed greatly among emotions, a noticeable difference ended up occurring in the number of data

points in clusters when clustering was performed under the same conditions.

The number of clusters for pleasure, sadness, anger and no emotion was thus set to 64, 64, 32 and 32, respectively, to result in the same ratio as the ratio of the four emotions of 1:1:2:2. And, as a result of examination, “100” was used as the threshold value in this study.

6. Evaluation Experiment

6.1 Experimental Method

The evaluation method 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.

Table 1 Result of the emotion judgment accuracy in the difference between the number of clusters and the threshold value.

Number of clusters (Pleasure, Sadness, Anger, No emotion)	32, 32, 16, 16	64, 64, 32, 32	128, 128, 64, 64	256, 256, 128, 128
Threshold value 0	27.4 %	28.9 %	28.3 %	29.5 %
Threshold value 50	30.6 %	28.2 %	28.7 %	26.7 %
Threshold value 100	29.3 %	33.0 %	30.2 %	30.7 %
Threshold value 150	30.2 %	30.8 %	31.9 %	28.6 %
Threshold value 200	26.7 %	30.2 %	30.2 %	29.2 %

Fig. 4 Result of emotion judgment from EEGs.

This study used a EEG feature knowledge base constructed by clustering all but the principal one of the 3436 EEG features obtained by excluding outliers from the total of 5040 EEG features described in Section 5.

6.2 Evaluation of Accuracy

Fig. 4 shows the result of emotion judgment from EEGs. Accuracy of emotion judgment from EEGs using the clustered EEG feature knowledge base was 33.0%. As a comparison, an emotion judgment system offered by a company that develops EEG measurement equipment [2] showed 27.9% accuracy. Moreover, an accuracy of emotion judgment system using the NOT clustered EEG feature knowledge base is 27.8%. The method proposed herein thus appears valid.

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

7. Conclusions

Authors are conducting research aiming to develop new interfaces that follow the mechanism of human communication, focusing on human common sense. Especially, authors focus on the emotion of which common sense and attempt to compose a method that judge the user's emotion, based on EEGs.

EEGs acquired from the subject are used as source EEGs. Spectrum analysis of the source EEGs to which emotion flags have been assigned is performed every 1.28 s, and the EEG features are determined. To judge emotion from EEGs, the distance between EEG features of the EEG to be judged and the data in the EEG feature knowledge base to which emotion flags have been assigned was determined in this study, and emotions were then judged. Emotions judged in this study were pleasure, anger, sadness, and no emotion.

Accuracy of emotion judgment was 33.0%, which is still low, but we believe we obtained sufficient clues that will lead to improved accuracy, such as the validity of knowledge base clustering. 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.

Acknowledgements

This research has been partially supported by the Ministry of Education, Science, Sports and Culture, Grant-in-Aid for Scientific Research (Young Scientists (B), 24700215).

References

- [1] Tsuchiya, S., Yoshimura, E., Watabe, H., Kawaoka, T., and Ren, F. 2010. "An Extraction Technique of Place-Related Words Based on an Association Mechanism." *International Journal of Knowledge Engineering and Soft Data Paradigms* 2: 4-14.
- [2] Yoshimura, E., Tsuchiya, S., Watabe, H., and Kawaoka, T. 2010. "Association Response by Understanding Commonsense in Conversation System." *Journal of Intelligent & Fuzzy Systems* 21: 49-55.
- [3] Tsuchiya, S., Imono, M., Yoshimura, E., and Watabe, H. 2012. "Emotion Judgment Method from a User Utterance Sentence." *International Journal of Knowledge-based and Intelligent Engineering Systems* 16: 11-6.
- [4] Yoshimura, E., Imono, M., Tsuchiya, S., and Watabe, H. 2012. "Automatic Detection of Illogical Adjective Phrase Based on Commonsense for Computer Conversation." *International Journal of Knowledge-based and Intelligent Engineering Systems* 16: 3-10.
- [5] Imono, M., Yoshimura, E., Tsuchiya, S., and Watabe, H. 2012. "The Degree of Association between Concepts Focusing on the Viewpoint." *Computer Technology and Application* 3: 801-7.
- [6] Imono, M., Yoshimura, E., Tsuchiya, S., and Watabe, H. 2013. "Proposing a Method of Generating Association Words from Multiple Words Based on Association System." *Journal of Communication and Computer* 10: 468-73.
- [7] Yoshimura, E., Imono, M., Tsuchiya, S., and Watabe, H. 2013. "Inference of the Day Topic Word using WWW Search Rankings for Computer Conversations." *Journal*

- of Communication and Computer* 10: 513-24.
- [8] Yoshimura, E., Imono, M., Tsuchiya, S., and Watabe, H. 2013. "Computer-generated Conversation Using Newspaper Headline." *Computer Technology and Application* 4: 387-94.
- [9] Clin, J. 1994. "Guideline Thirteen: Guidelines for Standard Electrode Position Nomenclature, American Electroencephalographic Society." *Neurophysiol* 11: 111-3.
- [10] Musha, T., Terasaki, Y., Haque, H. A., and Iranitsky, G. A. 1997. "Feature Extraction from EEG Associated with Emotions." *Art Life Robotics*: 15-19.