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Emotion Judgment System by EEG Based on Concept Base of EEG Features

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Abstract

This paper proposes an emotion judgment system by using an electroencephalogram (EEG) feature concept base with premise of noises included. This method references the word concept association system, which associates one word with other plural words and decides the relationship between several words. In this proposed emotion judgment system, the source EEG is input and 42 EEG features are constructed by EEG data; the data are then calculated by spectrum analysis and normalization. All 2945 EEG data of 4 emotions in the EEG data emotion knowledge base are calculated by the degree of association for getting the nearest EEG data from the EEG feature concept base constructed by 2844 concepts. From the experiment, the accuracy of the proposed system was 55.9%, which was higher than the support vector machine (SVM) method. As this result, the chain structured feature of the EEG feature concept base and the efficiency by the calculation of degree of association for EEG data help reduce the influence of the noise.

Keywords

electroencephalogram; EEG; emotion judgment; concept base; calculation of degree of association

1 Introduction

Recently, the studies of judging human's emotions by analyzing bio-information have been attracting attention and have become popular [1]. Emotions are known to have strong relation to the amygdala in the limbic system of the brain, and the relationship between emotions and the brain are being studied [2]. Emotions are immanent acts, therefore, it is difficult to cognize hormonal changes from external changes like expression or behavior. For example, sometimes people smiles to make other people not worry, even having "sad" emotion. Accordingly, judging an immanent act is required for understating real emotion.

There are several measurement techniques for the brain, such as near infrared spectroscopy (NIRS), magnetoencephalography (MEG), and functional magnetic resonance imaging (fMRI). However, electroencephalogram (EEG) can measure with simplified equipment and less burden to users. The EEG emotion judgment is expected to be widely used, for example in medical care, in the near future. Owing to this, we need to consider the scenes of usage in daily life for getting emotion from usual action. Although it is not a controlled environment [2] for getting EEG for researches, and only using one type of bio-information [3] thus far, it is eligible for getting EEG with simplified equipment in daily life. However, it is difficult to prevent contamination of noise without a controlled environment, which has an impact on the accuracy of EEG analysis. Some noises are possible to be rejected by signal processing technology, although it is difficult to reject all the noises completely, even in a controlled environment.

Therefore, this paper proposes an emotion judgment system by EEG with premise of noises included. This system is referring to the word concept association system [4], proposed for natural language processing. The word concept association system is constructed to realize word-to-word association and judge the relevance between several words at the computer. This system is possible to get appropriate words even noises are included. The word concept association system is constructed by a concept base and the calculation of degree of association. The concept base [5] is a large-scale database that is constructed both manually and automatically using words from multiple electronic dictionaries. The calculation of degree of association [6] calculates the nearness of word meaning quantitatively, by using structure of the concept base. Natural language processing has a similar problem with word contamination, but the calculation of degree of association surmounts the problem by using the concept base to calculate efficiently.

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This method for quantifying the nearness between words in natural language processing is reported to have better performance than the vector space method [7].

The proposed emotion judgment system in this paper is robust in noise, using a concept base of EEG features and the calculation of degree of association similar to that in the word concept association system. This proposed system replaces the word in word concept association system by EEG features. This paper compare the proposed system with the system using the support vector machine (SVM) [8], which known as high performance for observing the efficacy.

2 Previous Research

There are various studies for using EEG to judge emotions, such as hedonic judgment from stress in daily life [9], sensibility evaluation by watching pictures [10], judgment of feeling by experiment in past [11], and emotion judgment by listening music [12]. The hedonic judgment from stress judges comfort or discomfort, while the sensibility evaluation by watching pictures judges like or dislike. Especially, many studies in emotion recognition are defined emotion as a valence and an arousal as a target of recognizing, which are difficult to understand which emotion is expressed intuitively [13]. These studies are similar by judging binary data. Furthermore, the judgment of feeling by experiment in past judges relax, pleasure, sadness, and anger, while the emotion judgment by listening music judges pleasure, sadness, anger, and happiness. The word "emotion" is used in all the studies, but its definition varies [14]–[19]. Although the research of emotion has been conducted for a long time in psychology and neuroscience, it is still difficult to define it exactly. Thus, a standard definition of emotion does not exist [19], [20]. The current research of engineering approaches is also facing difficulty of defines "emotion" quantitatively [21]. Therefore, this paper regards comfort/discomfort, feeling, excitement, concentration, and anxiety as affection, and pleasure, anger, sadness, and fear as emotions of high order than affection.

Similar to the emotions we define in this paper, there are two methods to quantify EEG: the emotion spectrum analysis and the emotion fractal-dimension analysis [22], [23]. The emotion spectrum analysis method proposed by Musha et al. [22] judges such emotions as anger/stress, pleasure, sadness, and relax by using EEG. The emotion fractal-dimension analysis proposed by Nakagawa [2] uses EEG to judge anger, pleasure, sadness, and relax. These methods use the data which EEG and emotions are paired. These data are acquired by test subjects, which trained how to imaging emotions to control them. This paper assumes to use the system in daily life, thus the data are acquired from non-trained test subjects by showing them one Japanese film.

Additionally, EEG is one kind of bio-information and noises are easily included. It is difficult to remove all noises completely even by trying policy of noise elimination [24], [25]. Therefore, the proposed system in this paper reduces the influence of noises, presupposing that noises are included rather than reducing noises themselves.

3 Overview of Proposed System

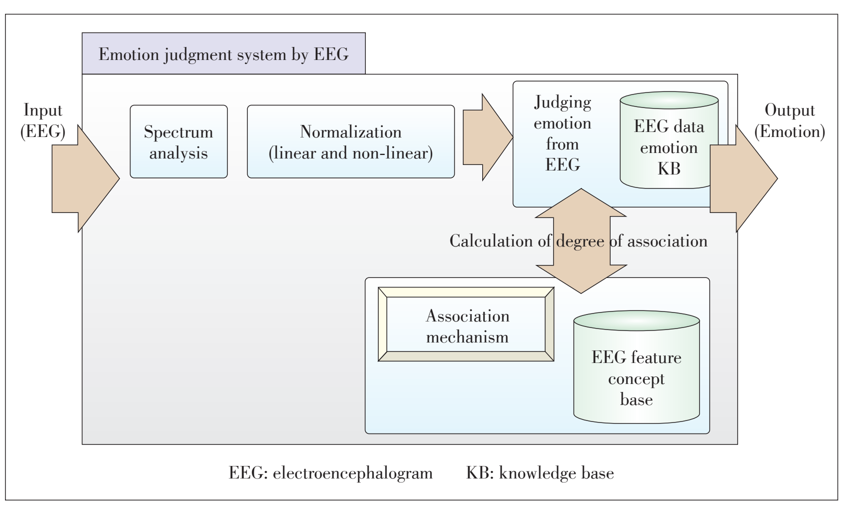
The objective of this proposed system is to obtain the emotions of conversation partners by reading their EEGs. **Fig. 1** outlines the proposed emotion judgment system by EEG.

EEGs acquired from the test subjects are used as source EEGs. Emotions of the subject are acquired simultaneously as source EEGs. Emotions are assigned to spectrum analysis of the source EEGs, which is performed every 1.28 second. The EEG features are determined to 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 30.0Hz), as shown in **Fig. 2**.

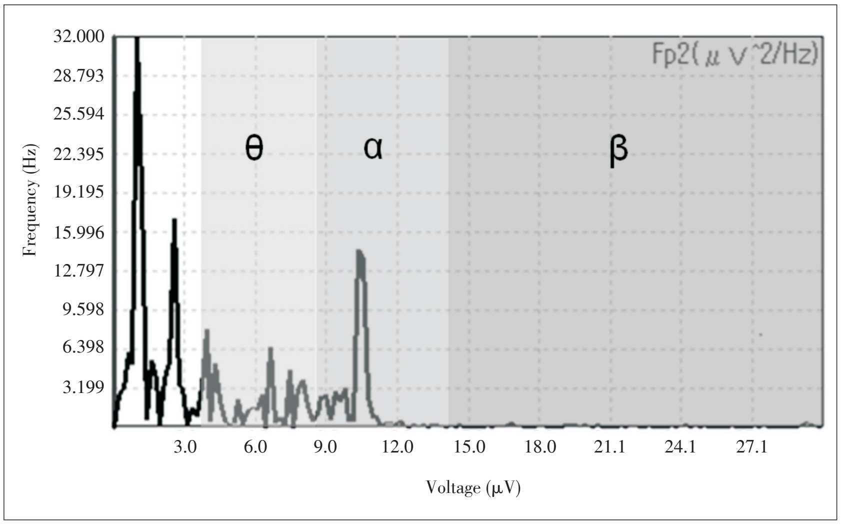
Emotions are judged from the EEG features by an association mechanism. The association of EEG Features is realized by using a huge concept base, which is automatically built from the EEG Features. The relationship between the EEG Features is evaluated by calculating the degree of association. The concept base and the degree of association are generally used for natural language processing; because the structure of EEG Features and that of the word in natural language processing are similar, we apply the technique in our system. Hereafter, this concept base and the calculation method are called the association mechanism. Emotions judged in the proposed system include pleasure, anger, sadness, and fear.

3.1 Source EEG and Emotion

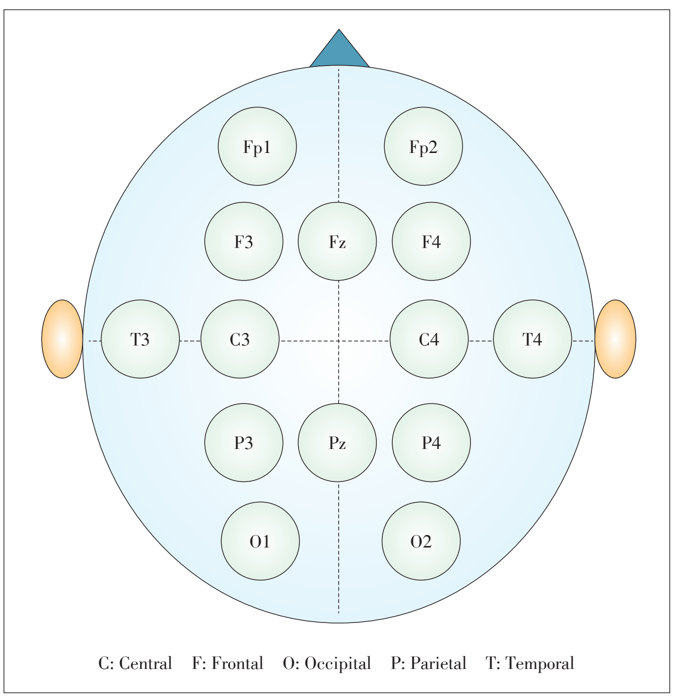
The EEGs were measured at 14 locations that conform to the International 10/20 System [26] (**Fig. 3**).



▲**Figure 1. Emotion Judgment System by EEG.**



▲**Figure 2. Spectrum analysis of the source EEGs.**



▲**Figure 3. EEG measurement at 14 locations, conforming to the International 10/20 System.**

The test subjects were fitted with electroencephalography caps [27] and asked to watch a Japanese film for approximately two hours. During the film watching, the subjects were asked to gauge the emotions they had felt by the speeches in the film, and the source EEGs were acquired simultaneously. The scene for a speech in the film was frozen, and the subjects were asked what emotions they felt at the time of watching the scene.

20 subjects (10 males and 10 females) were used, and the viewing was divided into four sessions to reduce the physical burden of the subjects. Before and after the film, the EEGs of open-eye and closed-eye states were respectively measured for approximately one minute for the normalization of EEG features.

3.2 EEG Features and EEG Data

The source EEGs are assigned to spectrum analysis and performed every 1.28 second. The EEG features are determined to take average of each wave: 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). The EEG features are made by average of 14 locations and 3 frequency bands, therefore, 42 EEG features are calculated from 1.28-second EEG.

3.3 Normalization of EEG Features

The EEGs show changes in voltage intensity over time within an individual, and the 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.

3.3.1 Linear Normalization

The linear normalization was performed because voltage intensity of EEGs varies over time depending on the subject. Since the eyes were open while viewing the film, linear normalization [28] was performed to acquire EEGs both before and after the experiment based on EEG features from the eye-open state. EEG features $Linear\_al_{ij}$ was obtained by linear normalization of the first EEG feature al_{ij} at a certain point of time during the experiment, and is expressed as:

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

where j HZ frequency is taken from the i-th location in electroencephalography caps and l blocks from the experiment start. The blocks are calculated by time that is divided by 1.28 seconds. P_1 is the time of the experiment start, and p_2 is the time of the experiment end. q_1 is the voltage when the experiment started, and q_2 is that when it ended.

3.3.2 Non-Linear Normalization

The non-linear normalization was performed to take into account the difference among individuals in base voltage intensity. The non-linear normalized values were obtained by using (2). $f(x)$ is the EEG features after the non-linear normalization [28], x is the EEG features applied in the non-linear normalization, x_{min} is the minimum EEG features of an individual, and x_{max} is his maximum EEG features. As a result, the EEG features with large values are compressed and EEG features with small value are expanded by the non-liner normalization. Thus, the degree of voltage intensity of an individual's EEGs is solved.

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

3.4 EEG Data Emotion Knowledge Base

The EEG data emotion knowledge base is a database constructed by EEGs and emotions. EEG features of 42 represented by three bandwidths are obtained from 14 locations and assumed to be one EEG datum, and the EEG data are matched with emotions, either anger, sadness, fear, or pleasure. The EEG data emotion knowledge base is consisted with the knowledge base of each emotion, and contains 2945 EEGs obtained by excluding the outliers and noises. The emotions of the 2945 EEGs are comprised 629 anger features, 857 sadness features, 979 fear features, and 480 pleasure features.

4 Association Mechanism

The association mechanism [5] consists of the concept base [6] and the degree of association [7]. The concept base generates semantics from certain EEG features. The degree of association is used for the semantics expansion, and it expresses the relationship between EEG features by a numeric value. The methods of a concept base and the degree of association were originally proposed for natural language processing, and are applied to the EEGs in this paper.

4.1 EEG Features Concept Base

The concept base [6] is originally a large-scale database that is constructed both manually and automatically using words from multiple electronic dictionaries. The entry words in dictionaries used as concepts and the independent words in the explanation under the concept are used as attributes. In the current research, a concept base contains approximately 90, 000 concepts, in which auto-refining processing is conducted after the base is manually constructed. In this process, attributes are considered from the point of view of human sensibility; the inappropriate attributes are deleted and necessary attributes are added.

In the concept base, Concept A is expressed by Attribute a_i, indicating the features and the meaning of the concept in relation to a Weight w_i, denoting how important Attribute a_i is in expressing the meaning of Concept A. Assuming that the number of attributes of Concept A is N, Concept A is expressed by (3), where Attribute a_i is called Primary Attribute of Concept A.

$$A=\{(a_1,w_1),(a_2,w_2),\cdots,(a_N,w_N)\}. \tag{3}$$

Because Primary Attribute a_i of Concept A is defined as the concepts in the concept base, attributes can be similarly elucidated from a_i. The Attributes a_{ij} of a_i are called Second Attributes of Concept A. Attribute a_i is defined by a_{ij}, and also defined as the concepts, so a_{ij} is Primary Attribute of a_i. Thus, the concept base can be connected to N-dimension.

In our work, the concept base is made by source EEGs instead of electronic dictionaries. In fact, EEG features are used instead of words. A word notation is used as a concept and an attribute in the concept base for natural language processing. However, notation of EEG features cannot be used as a concept and an attribute, as it is in the EEG feature concept base. A location and a frequency band cannot be discriminated from a concept, which is made by a notation of EEG Features. Additionally, EEG features are finite decimals, which describe finely than word notation, and are difficult to make chain structure. Therefore, to keep the information of location and frequency band in EEG Features in the concept base, we defined concept (attribute) notation as follow:

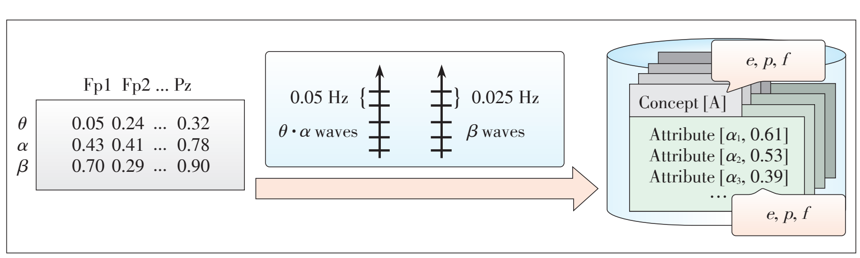
$$x_i=(e_i,p_i,f_i), \tag{4}$$

where x_i is the concept notation, e_i is an EEG Feature, p_i is an electrode part, and f_i is the frequency band. The EEG Feature is the voltage value in each location and each bandwidth is considered to be a part of the word respectively. However, the granularity of the voltage value is having more information than that of the word. Therefore, the voltage values in the certain scope are treated as the same (**Fig. 4**). As a result, the number of EEG features are controlled, similar to words that are controlled by synonyms. The concrete method is to delimit the θ waves and α waves by 0.05 μV, and delimit β waves by 0.025 μV. Furthermore, different numerical values in each divided group are allocated in the same part and bandwidth. A numerical value is treated as a word, and part and bandwidth are new information that is not used for natural language processing. As a result, EEG Features can be conceptualized similar to a concept base of words.

4.2 Weight

Weight [29], [30] is performed by the method of term frequency−inverse document frequency (TF-IDF). TF-IDF is popularly used in the field of natural language processing for searching information. Weight $W(A,B)$ of Concept A for attribute B, is calculated as follows:

$$W(A,B)=tf(B)\times\log_2\frac{D}{df(B)}. \tag{5}$$



▲**Figure 4. Process for conceptualization of EEG features.**

Concept A is one EEG feature out of 42 EEG features, and the remained 41 EEG features are considered as one attribute. the EEG features in the same group (Fig. 4) are also added to attributes. As the premises, $tf(B)$ expresses the frequency that comes out from all the attributes of Concept A. D is the number of concepts stored in EEG features concept base, and $df(f)$ is the number of concepts with Concept A included in each attribute. idf is calculated to divide D by $df(B)$, having logarithm as 2 for bottom.

4.3 Calculation of Degree of Association for EEG Feature

4.3.1 Degree of Match by Weight Ratio

The degree of match by the weight ratio is calculated by the total value of each EEG feature's degree of match. Regarding the input EEG as Concept A, and the EEG in the EEG data emotion knowledge base as Concept B. Each EEG's features of concepts are regarded as A' and B', and attributes are defined as a_i and b_i. Weights of A' and B' are defined as u_i and v_i. If the numbers of attributes are L and M respectively to the concepts ($L \leqslant M$) A' and B' can be expressed as follows:

$$A' = \{(a_1,u_1),(a_2,u_2),\cdots,(a_L,u_L)\}, \tag{6}$$

$$B' = \{(b_1,v_1),(b_2,v_2),\cdots,(b_M,v_M)\}. \tag{7}$$

EEG features e, electrodes part p, and frequency f are defined by a_L and b_M as follows:

$$A_L = (e_L,p_L,f_L), \tag{8}$$

$$B_M = (e_M,p_M,f_M). \tag{9}$$

Therefore, the degree match by the weight ratio $DoM(A',B')$ of Concepts A and B is calculated as follows:

$$DoM(A',B') = \frac{(S_{A'}/n_{A'} + S_{B'}/n_{B'})}{2} \times \frac{\min(u_i,v_j)}{\max(u_i,v_j)}, \tag{10}$$

$$S_{A'} = \sum_{a_i=b_j} u_i , \quad S_{B'} = \sum_{a_i=b_j} v_j, \tag{11}$$

$$n_{A'} = \sum_{i=1}^{L} u_i , \quad n_{B'} = \sum_{j=1}^{M} v_j, \tag{12}$$

$$\min(u_i,v_j) = \begin{cases} u_i(u_i \leqslant v_j) \\ v_j(u_i > v_j) \end{cases}, \tag{13}$$

$$\max(u_i,v_j) = \begin{cases} u_i(u_i > v_j) \\ v_j(u_i \leqslant v_j) \end{cases}. \tag{14}$$

When the attributes match, $a_{ij} = b$. $S_{A'}$ is the total weight of a_i when $a_i = b_j$, and $S_{B'}$ is the total of b_j when a_i=b_j. $n_{A'}$ and $n_{B'}$ are the total weights of Concepts A and B. Thus, $S_{A'}/n_{A'}$ is the ratio of weight that is matched to the attribute looking from Concept A, and $S_{B'}/n_{B'}$ is the ratio of weight that is matched to the attribute looking from Concept B. Therefore, $(S_{A'}/n_{A'} + S_{B'}/n_{B'})/2$ expresses average of $S_{A'}/n_{A'}$ and $S_{B'}/n_{B'}$. The degree of match by the weight ratio is calculated by considering the ratio of coincidence of the attribute and the weight.

4.3.2 Degree of Association by Weight Ratio

The degree of association by weight ratio is used in this paper to consider the coincidence of the attribute and the weight. For calculation, the input EEG data and the EEG data emotion knowledge base data, i.e. para-concepts A and B, use para-concept A' as a base to fix the row. Para-concept is a one block of concept, and the EEG features in this block becomes the first attribute. Then, the attributes in para-concept B are sorted for making the total of the degree of match largest between para-concepts B and A. The attribute and weight of para-concept B is defined as (b_{xi}, v_{xi}). The electrode part p_{xi}, frequency band f_{xi}, and EEG features e_{xi} are defined by b_{xi}.

$$B' = \{(b_{X1},v_{X1}),(b_{X2},v_{X2}),\cdots,(b_{X42},v_{X42})\}, \tag{15}$$

$$b_{Xi} = (e_{Xi},p_{Xi},f_{Xi}). \tag{16}$$

In this study, 42 EEG features represented by three bandwidths, are obtained from 14 locations and assumed to be the attributes. They are used by the calculation of the degree of association. Such the calculation for EEG features expresses the relationship between EEG features. The purpose of this research is to compare EEG data for judging emotions. To realize comparison of EEG data, the para-concept is used and the calculation of the degree of association is extended. We regard EEG data as a Concept, and 42 EEG Features as the Attributes to calculate the degree of association. To create the para-concept, the attributes (EEG features) need to calculate weight, thereby we assume the weight of attribute as 1 evenly.

Additionally, a concept base can generally expands to top 30 attributes, however the EEG data constructed by 42 EEG features, therefore this research expands top 42 attributes.

5 Emotion Judgments from EEGs

The input data is the source EEG; therefore it is calculated by spectrum analysis and normalizations. From the calculation, the EEG data created from 42 EEG features are obtained. The EEG data are calculated by the degree of association for EEG features with all 2945 EEG data in the EEG data emotion knowledge base, categorized in four emotions, i.e. anger, sadness, fear, and pleasure.

By using the EEG features concept base, we can calculate the nearness of EEG data for reducing the influence of noises. The EEG feature concept base is a concept base constructed from EEG 2844 features. One EEG feature in the EEG feature concept base (concept) is realized by other EEG features (attribute) that co-occur and are related. In addition, these EEG features are also realized by other EEG features; therefore the EEG feature concept base can connect to N-dimensions and realize the chain structure. The weight of attribute is denoting how important an attribute is in expressing the meaning of concept, and this is one element for reducing the noise.

After acquiring EEG data with the highest degree of association, get an emotion linked to EEG data from EEG data emotion knowledge base. An acquired emotion is outputted as the emotion of the input EEG data.

6 Calculation Experiment

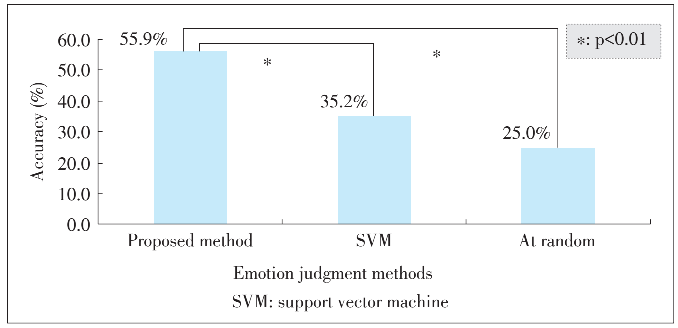
6.1 Experiment Method

The method of evaluation is leave-one-out-cross-validation, a technique that involves using one data extracted as the validation set and the remaining observations as the training set for comparison. Therefore, one EEG data that take from EEG data emotion knowledge base stand for input data, and rest of all in EEG data emotion knowledge base is stand for target EEG data. In this study, the EEG data emotion knowledge base contains 2945 EEGs from 20 subjects (10 males and 10 females). The emotions of the 2945 EEGs are comprised 629 anger features, 857 sadness features, 979 fear features, and 480 pleasure features.

SVM, one of the high-performance classification methods, was chosen as a comparative method. Among the SVM methods, Lib-SVM [9] was chosen since it is widely known. As for the proposed system, one data set is extracted from the EEG data emotion knowledge base as the validation set and the remaining observations from the EEG data emotion knowledge base are treated as the training set for comparison. There are some variations of parameters in SVM, so Lib-SVM performed with default values the developer had recommended.

6.2 Results

The results of the emotion judgment from EEGs are shown in **Fig. 5**. The accuracy of emotion judgment from EEGs using the association mechanism was 55.9%. As a comparison, the accuracy by the SVM method was 35.2%, and the accuracy of emotion judgment at random was 25.0%. For these results, the chi-squared test (degree of freedom 1, $p<0.01$) was performed, and the proposed system was statically significant from the other two methods.



▲**Figure 5. Comparison of accuracy of the emotion judgment methods.**

7 Discussions

It can be seen that the accuracy of the emotion judgment system by EEG using the EEG feature concept base is better than that of SVM system. The proposed system can judge higher accuracy of the nearness of EEG features. The chain structure is realized by constructing the EEG features concept base. The pair of EEG features and the weight are expressing the concept in EEG Features Concept Base, and these EEG features are also expressed by the different group of the pair by EEG Features and weight. SVM depends on learning data, therefore, noises may make big influence if they are included in the learning data. That is why the SVM method has low accuracy.

Although the accuracy of the proposed system and SVM had significant difference, the learning data was not enough for SVM, which has strong effect on accuracy. Therefore, if the learning data increases, SVM has a potential to increase the accuracy. For increasing learning data, it takes high cost and unrealistic. With these qualifications, proposed system was acquired enough result.

The weight of the para-concept is defined as 1 evenly in this paper, however there is possibility of accuracy improvement by changing the weight for each para-concept. Previous studies have estimated the cognitive load with combination of frequency band and electrode parts [31]–[33]. There are possibilities for choosing a more appropriate weight than an even value if these combinations are taken into account in weight setting.

8 Conclusions

In this paper, an emotion judgment system was proposed by using the EEG feature concept base to reduce the influence of noises, with premise of noises included. This system is referring to the word concept association system for natural language processing. The experiment results show that the accuracy of proposed system is 55.9%, much better than that of SVM, one of the classification methods in high performance. From this result, we believe that the proposed method is effective to reduce the influence of noises by utilizing chain structure of the EEG feature concept base and effective calculation of the degree of association for EEG features. Therefore, this method can improve the accuracy of emotion judgment.

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