

# Study on Arousal Recognition Method Using Electroencephalogram (EEG) Signals

Human and Engineered Environmental Studies

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Graduated on September 26th, 2014

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Improving arousal recognition accuracy based on EEG signals is important for emotion recognition. In this research, discrete wavelet transform was employed to extract features and cross-level method was proposed to select effective features. Cross-level method showed a great potential for 2-level arousal classification and the recognition accuracy reached to 91.8%. Besides, sensitivity of EEG channels is also discussed based on two ranking methods of SCP (single-channel performance) and ANOVA (analysis of variance). Finally, arousal recognition method based on EEG signals is applied for constructing Japanese emotion database.

Key words: Arousal recognition, EEG, DWT (discrete wavelet transform), Channel selection

## 1. Introduction

Nowadays, human emotion plays a significant role in our lives, such as healthcare and human-computer interaction (HCI). However, researchers still have many discussions about emotion recognition technologies. Since the arousal-valence (A-V) space as shown in Fig. 1 was proposed in 1980<sup>1</sup>, it has been accepted in emotion related studies.

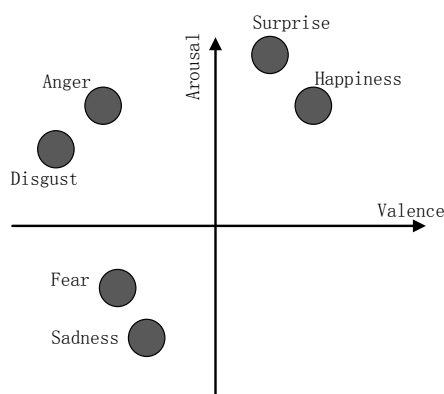


Fig. 1 Distribution of emotions on A-V space

As a way to study emotion states from brain activities, electroencephalography (EEG) signals have been used in various fields. In the study of valence recognition, S. A. Hosseini et al. adopted entropy analysis of EEG signals and achieved 2-level valence recognition rate of 72.35%<sup>2</sup>. With a proposal of cross-level feature selection method, H. Zhang et al. improved the recognition accuracy to 98% for 2-level model and 90% for 3-level model<sup>3</sup>, and showed that cross-level method is effective in valence recognition. On the other hand, for arousal recognition, Y. Liu et al. used EEG signals collected from 44 electrodes and the 2-level recognition rate of arousal reached to 76.51%<sup>4</sup>. In the experiment conducted by M. Soleymani et al., 216 features were extracted from 32 electrodes, and the 3-level recognition rate of arousal was 52.4%<sup>5</sup>. However, no effective feature selection method was

mentioned. Moreover, electrode selection method was also not mentioned in previous studies on arousal recognition. According to the experiment of L. I. Aftanas et al., the right posterior area of the cortex shows a greater relationship with arousal than others<sup>6</sup>. However, H. J. Yoon et al. think that EEG signals recorded from T7, T8, C3, C4 electrodes are effective in discerning arousal<sup>7</sup>, so that the effective electrodes for arousal recognition are still not clear and more efforts are needed.

## 2. Purpose and target

The research purpose is to propose an effective arousal recognition method using EEG signal and to apply it for constructing Japanese emotion database.

There are two research targets need to be achieved. The first one is to propose a procedure of arousal recognition including feature selection and electrode selection. The second one is to apply the method on database validation.

## 3. Arousal recognition procedure

The procedure for arousal recognition consists of 4 steps, including raw signal acquisition, feature extraction, feature selection and classification.

### 3.1 Raw signal acquisition

The data used in this section is from the first part (Part I) of Japanese emotion database. In constructing the database, pictures from International Affective Picture System (IAPS) were used as stimuli while EEG signals being recorded. The sampling rate of raw EEG signals was 1 kHz. Corresponding to each picture, 10-second EEG signals are recorded in 16 channels.

### 3.2 Feature extraction

To utilize EEG signals for arousal recognition, 7-level DWT is applied on raw EEG signals. With detail coefficients and approximation coefficient decomposed, data from 8 frequency bands, such as (250-500Hz), (125-250Hz), Upper  $\gamma$  (63-125Hz), Lower  $\gamma$  (31-63Hz),  $\beta$  (16-31Hz),  $\alpha$  (8-16Hz),  $\theta$  (4-8Hz) and  $\delta$  (0-4Hz),

are obtained from the raw EEG signals. For the coefficients from each DWT level, statistical features of standard deviation (STD), mean, skewness and kurtosis are extracted.

### 3.3 Feature selection

To select sensitive features for arousal recognition, mono-level and cross-level methods are compared.

#### 3.3.1 Mono-level feature selection

The same DWT level, from which features are extracted, is selected for 16 electrodes. In this method, one certain DWT level will be chosen. However, for different subjects, the certain DWT level may be different.

#### 3.3.2 Cross-level feature selection

One DWT level, from which features are extracted, is selected independently for 16 electrodes. In this method, Genetic Algorithm is also applied to select an optimal DWT level set.

Fig. 2 shows an image of DWT level selection method (mono-level method and cross-level method). After selecting DWT levels, a statistical feature such as STD is extracted from selected DWT levels. Then, a feature vector is constructed by the statistical features of 16 channels.

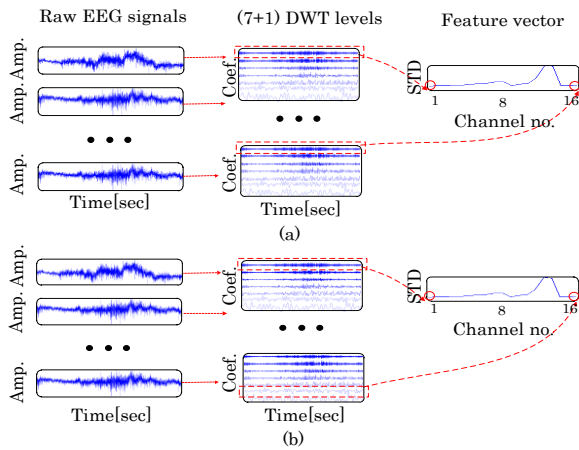


Fig. 2 DWT level selection method (a) Mono-level method. (b) Cross-level method.

### 3.4 Classification

Probabilistic neural network (PNN) is adopted as the classifier, because it costs little time for training. In this research, subject-dependent model is applied and the PNN classifier is trained separately for each subject. The arousal recognition accuracy for each subject is obtained by using the leave-one-out crossing validation.

### 3.5 Results and discussion

The result of 2-level arousal recognition is shown in Fig. 3. Compared with other statistical features, STD performs the best with the average accuracy of 91.8%. Moreover, cross-level method shows a greater potential than mono-level method. In the case of cross-level, the average accuracy is always much higher than that of

mono-level for all the statistical features.

For 3-level arousal recognition, with cross-level method, and STD extracted as feature, the average accuracy reaches to 73.4%.

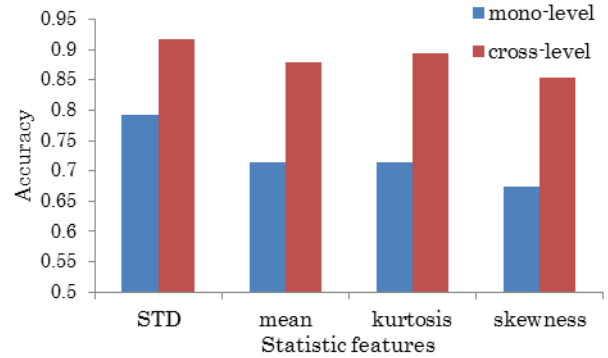


Fig. 3 Arousal recognition accuracy for 2-level using mono-level and cross-level methods for DWT level selection

## 4. EEG channel selection in arousal recognition

Arousal related EEG channels are also discussed in this research. To study the optimal channel groups for arousal detection, 2 methods of SCP and ANOVA are applied to obtain the ranking of 16 channels and it will be used for selecting the optimal channel groups and common channels.

### 4.1 Single-channel performance (SCP)

Similar to the procedure employed for cross-level method, 7-level DWT and PNN are adopted to compute SCP. However, the input signal is not from 16 channels but from one channel. In this way, one feature from a certain DWT level will be selected instead of the feature vector mentioned in Fig. 2. The output accuracy from PNN classifier could show the sensitivity of the channel for arousal recognition. According to the results from each channel, a SCP ranking of the whole channels is calculated for each subject.

### 4.2 Analysis of variance (ANOVA)

ANOVA is a method to analyze the differences between groups by using means and their associated procures. For applying ANOVA, the EEG signals of 10 pictures for each level are assigned into 10 groups. Such assignment is conducted based on the arousal values of the corresponding pictures. In this research, three cases are considered:

- Case 1: The EEG signals in each arousal level are sequenced in ascending order of arousal values.
- Case 2: The ascending order for the high arousal level, but the descending order for the low arousal level is adopted.
- Case 3: A random order is adopted for each arousal level.

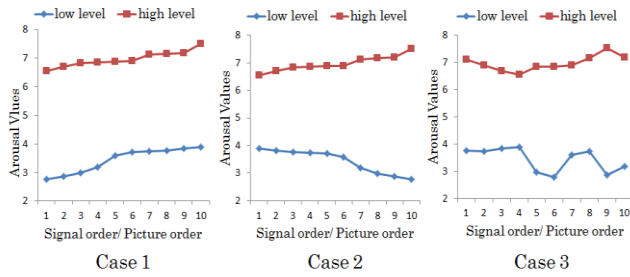


Fig. 4 Order of EEG signals in 3 cases of ANOVA

Signals with the same order in each level are assigned into the same group. 7-level DWT is also applied to help decompose the raw signals. With significance in computing set to be 0.05, the distinguishable results are accumulated from 10 groups. Result from the DWT level which achieves the highest score is used as the final ANOVA confidence. Thus, ANOVA ranking of 16 channels can be established. In this way, besides the SCP ranking, the other 3 rankings are obtained from Case 1, Case 2 and Case 3, respectively.

#### 4.3 Common channels

Statistical analysis is conducted on these 4 rankings (from SCP and ANOVA) and sensitive score is computed for each channel (Fig. 5). Considering the similar results of 3 cases from ANOVA method, ANOVA case 1 is used for the latter analysis.

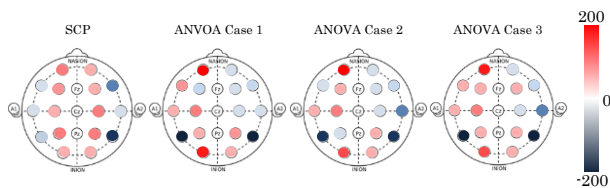


Fig. 5 Sensitive score of 16 channels based on SCP and ANOVA. Higher score in the positive direction (red) means more sensitive to arousal.

According to Fig. 5, three areas of channels show higher sensitivity than other channels: Channel Fp1 in the left front area, Channel C3 in the left temporal area, Channel O1, O2, P4 in the posterior of the cortex. Such a finding is partly compatible to the conclusions from previous neuroscience studies mentioned in Introduction.<sup>6)7)</sup> From the sensitive performance for 50 subjects, the common channels, including Fp1, C3, O1, O2 and P4, prove to be effective in arousal recognition and will be used in the latter section of this research.

#### 4.4 Optimal channel groups

Different from common channels, the optimal channel groups are constructed based on the accuracy-oriented rules. According to the rankings of SCP and ANOVA, arousal recognition performances are computed on channel groups of 1 channel to 16 channels, and the results show that 10-channel group achieves the highest accuracy in 2-level arousal recognition. Then, a table with subject-dependent 10

channels is constructed and called as the optimal channel groups.

#### 4.5 Arousal recognition performance on different EEG channel sets

As the last part of channel selection, 2-level arousal recognition performance is computed for the further discussion on different EEG channel sets.

The important channel groups in Fig. 6 are the optimal channel groups and common channels. In the case of common channels, with EEG signals from only 5 channels, 2-level arousal recognition accuracy is similar to that of 16 channels. Therefore, the common channels are suitable for database validation.

Considering the performance of the optimal channel groups for 2-level arousal recognition, such subject-dependent channel information will be employed to help select the typical emotional data.

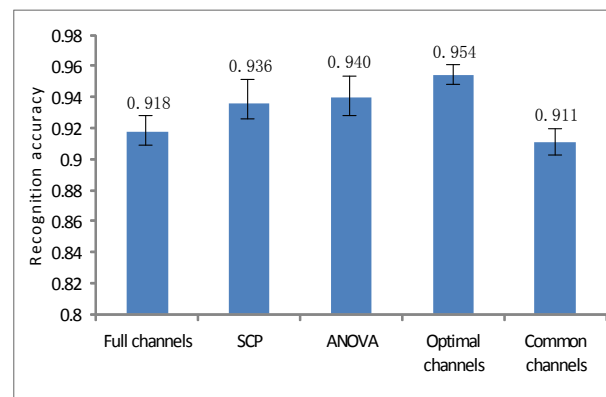


Fig. 6 2-level arousal recognition accuracy for different EEG channel sets

## 5. Database validation

Database validation is applied on Part II (original database) of the Japanese emotion database, of which the emotional signals are induced by self-recall experience by each subject. Database validation consists of two steps: select good data from original database and then evaluate the quality of the selected database. EEG based database validation method is proposed in this research, by using the results of former sections.

#### 5.1 Data selection

With the optimal channel information, including optimal channel groups and the corresponding effective DWT levels, the procedure of data selection is shown in Fig. 7.

According to the channel information, the typical feature vectors for both high arousal and low arousal are obtained for training the 2-level PNN classifier. Similar process is also conducted on testing EEG signals of the original database. After 0-1 normalizing and extracting feature vector from testing EEG signals, the feature vector is input to PNN. Based on the distribution of emotions in A-V space, 6 emotions can be classified into two arousal levels. If the classification

results of PNN meet the arousal level of A-V space, the signal is believed to be good and is accepted for constructing the selected database. Applying this selection method, about half of the data are accepted to the selected database from the original database.

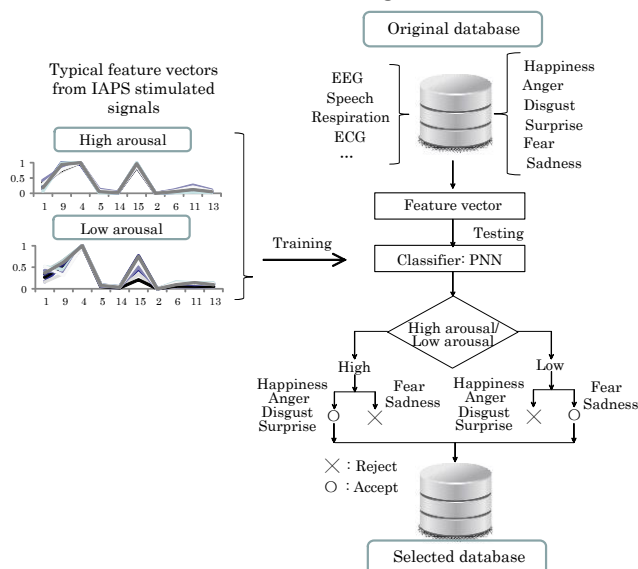


Fig. 7 Procedure of data selection

## 5.2 Evaluation of database quality

2-level arousal recognition method is employed for evaluating the quality of selected database. 360 pieces of signals, 60 for each emotion, are selected randomly from original database to be used as testing signals. Another 900 pieces of signals are selected separately from original database and selected database to train the PNN classifier. As the first step in processing those signals, EEG signals recorded in 5 common channels (Fp1, C3, O1, O2 and P4) are decomposed by 7-level DWT. Then standard deviation (STD) is extracted from each frequency component (DWT level). Using PNN as classifier, the recognition accuracy for each emotion is collected. After repeating such procedure for ten times, the average results are calculated and shown in Fig. 8.

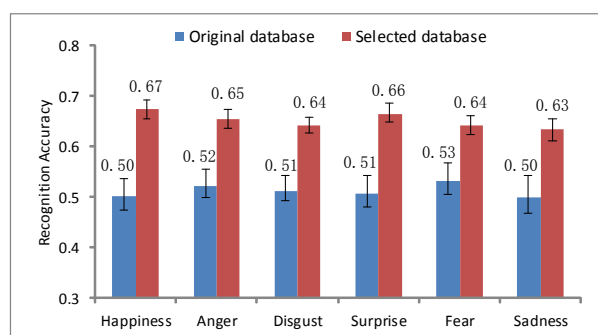


Fig. 8 Recognition accuracies using original and selected databases

The recognition accuracy can be regarded to reflect the quality of corresponding training database. As shown in Fig. 8, a great difference in 2-level arousal

recognition performance appears among these two databases. The quality of selected database is obviously higher than that of original database. Such result also proves that the EEG based data selection method is an effective way to improve the quality of emotion database.

## 6. Conclusion and future perspectives

As an important section on affective computing, arousal related studies on EEG signals have been carried out in this research. By applying cross-level feature selection method and the optimal channel groups, the recognition accuracy for 2-level arousal recognition has been improved to 95.4%, which is much higher than previous studies.

Secondly, the discussion on common channels is fulfilled based on two rankings of SCP and ANOVA. Common channels also show a good performance of 91.1%. This result provides some ideas for further study on arousal related sensitive channels.

Finally, in database validation, EEG based data selection method is useful to select the typical emotional data from original database. And this method is proved to be effective by evaluating the quality of selected database.

However, there are still some points need more efforts:

1. Other arousal related features. In this research, four kind of statistical features are discussed for detecting arousal status. However, there are still some other features not mentioned, and some of them may be also effective in arousal recognition.
2. For common channels, 5 channels are simply selected out of 16 channels. However, the other channel combinations are not studied. Further study on this point may result in more significant information.

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