# Arousal Recognition Method using Electroencephalography Signals to Construct Emotional Database

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Abstract: Improving arousal recognition accuracy by using EEG signals is important for emotion recognition. In this research, discrete wavelet transform is used to extract features, and a cross-level method is adopted to select effective features. The cross-level method shows great potential for two-level arousal classification, and the recognition accuracy reaches 91.8%. The 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 to construct a Japanese emotion database.

## 1 INTRODUCTION

Human emotion plays a significant role in daily life. Effective communication requires both verbal information and emotion. Sharing one's emotions is helpful as a way of understanding one's true ideas. In healthcare, emotion regulation is also very important when dealing with certain diseases, like mental disorders. Positive emotions have proved to be effective to help patients recover from illness. For human-computer interaction (HCI), analysis of human emotion can help establish fluent communication between computers and humans. For this, emotion recognition can be used in various fields in various ways.

Such importance has led to a lot of research on analysis of human emotion in recent years. Based on signal analysis, several kinds of signals have been used to help study emotions. Previous studies show that emotions are the result of cognitive processes (Sander et al., 2005). Collected from the brain, EEG signals can reflect brain activity and be used to obtain emotion-related information. In this research, EEG signals have been selected for arousal-related study.

The selection of target emotions is another very important issue in emotion recognition. A six-emotion group consisting of happiness, anger, disgust, surprise, fear, and sadness has been studied by many researchers (Ekman et. al., 1972). In this research, this emotion group is also used. For emotion recognition, many models are available in the field of affective computing. T. Musha (Musha et al., 1997) used a four dimensional feature vector to represent four kinds of emotions (joy, anger, sadness, and relaxation). However, one of the most popular models for emotion-related study is based on the arousal-valence (A-V) space as shown in Figure 1. Since this model was first proposed, valence (positive and negative) and arousal (passive and active) have been accepted by many researchers to represent different emotions. It has been developed a lot, and the relative positions of several kinds of emotions have been studied (Russell, 1980).

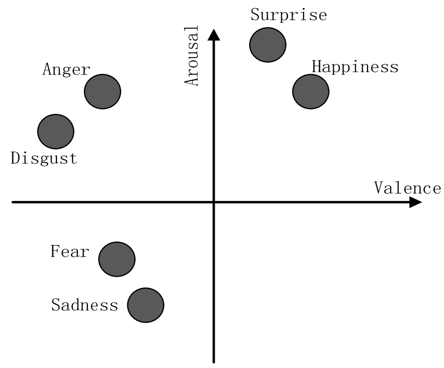


Figure 1: Distribution of emotions on A-V space.


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In the study of valence recognition, S. A. Hosseini et al. adopted entropy analysis of EEG signals and achieved a two-level valence recognition rate of 72.35% (Hosseini et al., 2011). With their proposed cross-level feature selection method, H. Zhang et al. improved the recognition accuracy to 98% for the two-level model and 90% for the three-level model (Zhang et al., 2014) and showed that cross-level wavelet features are effective for valence recognition. On the other hand, for arousal-related studies, Y. Liu et al. used EEG signals collected from 44 electrodes in an experiment. The two-level recognition rate of arousal reached 76.51% (Liu et al., 2012). In the experiment conducted by M. Soleymani et al., 216 features were extracted from the data collected with 32 EEG electrodes, and the three-level recognition rate of arousal was 52.4% (Soleymani et al., 2012). Although different methods have been adopted in previous studies, effective method for feature selection still puzzles a lot of researchers. Moreover, arousal-related EEG channels also need to be studied more. Previous study with fMRI analysis shows that the arousal recognition performance of the left and right hemisphere of the brain is different, especially for the occipital region (Lang et al., 1998). In accordance with the experiment designed by L. I. Aftanas et al., the right posterior area of the cortex shows a greater relationship with arousal than other areas (Aftanas et al., 2004). However, the result of H. J. Yoon's study indicates that EEG signals recorded at the T7, T8, C3, and C4 electrodes can discern arousal effectively (Yoon et al., 2011). Earlier studies on the asymmetry function of the brain show that arousal-related indices are more dependent on the right than the left hemisphere (Lane et al., 1995; Wittling, 1995).

# 2 AROUSAL RECOGNITION PROCEDURE

## 2.1 Raw Signal Acquisition

The data used in this section is from the IAPS-stimulated Japanese emotion database. In constructing the database, pictures from the international affective picture system (IAPS) were used as stimuli while EEG signals being recorded with 1 kHz sampling frequency. The subjects were asked to refrain from blinking their eyes and the line noise was filtered at 50Hz during the experiments in order to reduce artifacts. Corresponding to each picture, 10-second EEG signals were recorded in 16 channels: Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, and T6 according to International 10-20 system (Figure 2). In this research, those channels were also remarked with the number from 1 to 16.

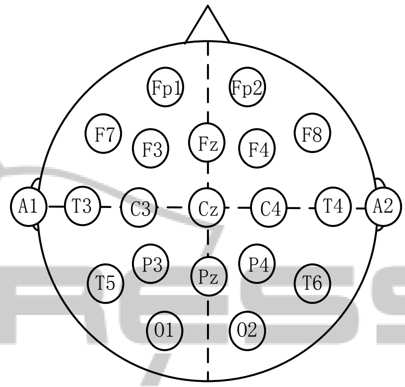


Figure 2: International 10-20 system (EEG).

## 2.2 Feature Extraction

To utilize EEG signals for arousal recognition, seven-level DWT was applied on raw EEG signals. With detail coefficients and approximation coefficients decomposed, data from eight frequency bands, 250-500 Hz, 125-250 Hz, upper $\gamma$ (63-125 Hz), lower $\gamma$ (31-63 Hz), $\beta$ (16-31 Hz), $\alpha$ (8-16 Hz), $\theta$ (4-8 Hz), and $\delta$ (0-4 Hz), were obtained from the raw EEG signals. For the coefficients from each DWT level, statistical features of standard deviation (SD), mean, skewness, and kurtosis were extracted.

## 2.3 Feature Selection

To select sensitive features for arousal recognition, mono-level and cross-level methods were adopted and compared. Both methods focus on the selection of effective frequency bands or DWT levels.

### 2.3.1 Mono-level Feature Selection

The same DWT level, from which features were extracted, was selected for 16 electrodes. In this method, one certain DWT level was chosen for all channels depends on the performance of arousal recognition. However, for different subjects, the certain DWT level may be different.

### 2.3.2 Cross-level Feature Selection

One DWT level, from which features were extracted, was selected independently for 16 electrodes. In this method, genetic algorithm was applied to select the optimal DWT level group.

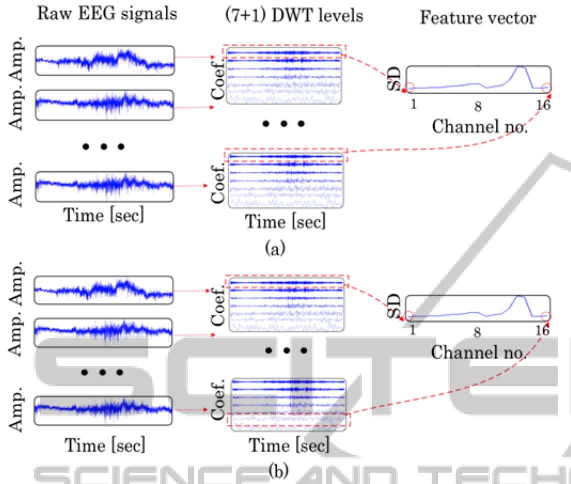


Figure 3: DWT level selection method. (a) Mono-level method (the same DWT level is selected for all EEG channels). (b) Cross-level method (different DWT levels are selected for different EEG channels).

Figure 3 shows a schematic of the DWT level selection method (mono-level method and cross-level method). After selecting DWT levels, a statistical feature such as SD was extracted from the selected DWT levels. Then, a feature vector was constructed by using the statistical features of 16 channels.

## 2.4 Classification

In this research, a subject-dependent model was applied. The arousal recognition accuracy for each subject was obtained based on the leave-one-out cross-validation with Probabilistic neural network (PNN). EEG signals (1000 samples) collected from 50 healthy Japanese subjects (35 males and 15 females) are used for the validation.

## 2.5 Results and Discussion

The result of two-level arousal recognition is shown in Figure 4. Compared with other statistical features, SD performed the best with an average accuracy of 91.8%. Moreover, cross-level feature selection showed greater potential than mono-level feature selection. With cross-level feature selection, the average accuracy was always higher than that of mono-level feature selection for all the statistical features.

For three-level arousal recognition, with the cross-level method and SD extracted as a feature, the average accuracy reached 73.4%.

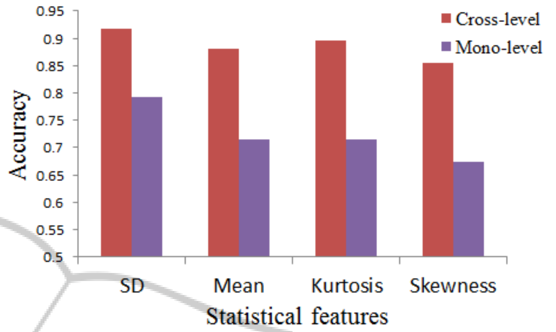


Figure 4: Two-level arousal recognition accuracy for applying mono-level and cross-level methods on DWT level selection.

# 3 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, two methods (SCP and ANOVA) were applied to obtain the ranking of the 16 channels, and it will be used to select the optimal channel groups and common channels.

## 3.1 Single-Channel Performance (SCP)

Similar to the procedure used for the cross-level method, the seven-level DWT and PNN were adopted to compute the SCP. However, the input signal was not from 16 channels but from one channel. In this way, one feature from a certain DWT level was selected instead of the feature vector mentioned in Figure 3. The output accuracy from the PNN classifier could show the sensitivity of the channel for arousal recognition. In accordance with the results from each channel, the SCP ranking of the whole channel was calculated for each subject.

## 3.2 Analysis of Variance (ANOVA)

ANOVA was applied to the EEG signals of 10 pictures for each level. Those signals were assigned to 10 groups. Such assignment was conducted based on the arousal values of the corresponding pictures. In this research, three cases were considered:

Case 1: The EEG signals in each arousal level were sequenced in ascending order of arousal values.

Case 2: The ascending order was adopted for the high arousal level, but the descending order was adopted for the low arousal level.

Case 3: A random order was adopted for each arousal level.

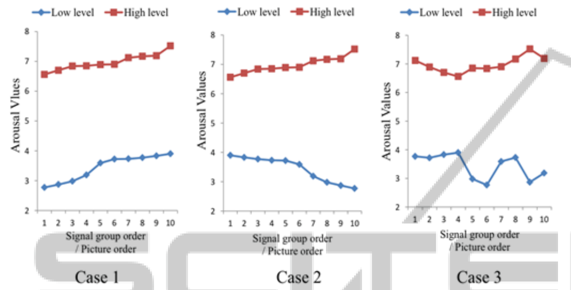


Figure 5: Order of EEG signals in three ANOVA cases.

Signals with the same order in each level are assigned to the same group. Seven-level DWT was also applied to help decompose the raw signals. With the significance in the computing set to 0.05, ANOVA was applied to the same coefficients (detail and approximate) from both the high arousal signal and the low arousal one, and the results are the sum of 10 groups for each DWT level. The result from the DWT level that achieved the highest score was used as the final ANOVA confidence. Thus, an ANOVA ranking of 16 channels could be established. In this way, besides the SCP ranking, the other three rankings were obtained from Case 1, Case 2, and Case 3.

## 3.3 Common Channels

Statistical analysis was conducted on these four rankings (from SCP and ANOVA), and a sensitive score was computed for each channel (Figure 6).

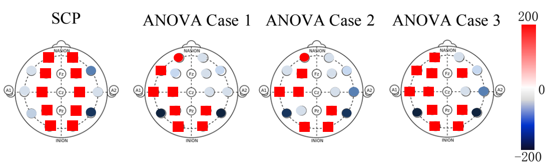


Figure 6: Sensitive score of 16 channels based on SCP and ANOVA. Higher score in positive direction (red) means more sensitive to arousal.

Considering the similar results of three cases from the ANOVA method, ANOVA Case 1 was used for the latter analysis.

In accordance with Figure 6, three areas of channels show higher sensitivity than other channels: Channel Fp1 in the left front area, Channel C3 in the left temporal area, and Channel O1, O2, P4 in the posterior of the cortex. Such a finding is partly compatible with the conclusions from previous neuroscience studies mentioned in the introduction (Aftanas et al., 2004; Yoon et al., 2011). From the sensitive performance for 50 subjects, the common channels, including Fp1, C3, O1, O2, and P4 proved to be effective in arousal recognition and will be used in the latter section of this research.

## 3.4 Optimal Channel Groups

Different from common channels, the optimal channel groups were defined based on the accuracy-oriented rules. In accordance with the rankings of SCP and ANOVA, arousal recognition performances were computed for channel groups of 1 channel to 16 channels, and the results indicate that 10-channel group achieved the highest accuracy for most subjects in two-level arousal recognition. The first 10 highest ranking channels were selected for each subject, as the optimal channels, to achieve higher recognition accuracy.

## 3.5 Arousal Recognition Performance for Different EEG Channel Sets

As the last part of channel selection, two-level arousal recognition performance was computed for further discussion on different EEG channel sets (Figure 7). For SCP and ANOVA, ten EEG channels were selected according to their rankings.

The important channel sets in Figure 7 are the optimal channels and common channels. In the case of common channels, with EEG signals from only 5 channels, two-level arousal recognition accuracy is similar to that of 16 channels. Therefore, the common channels are suitable for database validation.

The optimal channels raise arousal recognition accuracy by about 4% compared to the common channels with $p<0.001$ by paired t-test. Considering the performance for two-level arousal recognition, such subject-dependent optimal channel information was used to help select the typical emotional data.

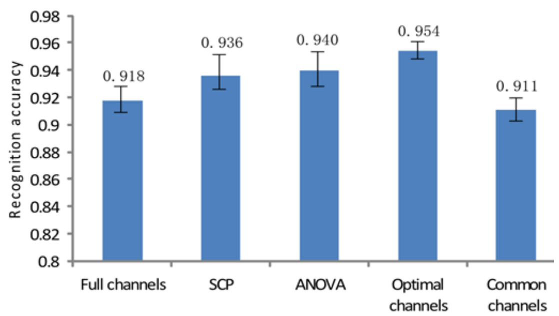


Figure 7: Two-level arousal recognition accuracy for different EEG channel sets.

# 4 DATABASE VALIDATION

Database validation was applied to the Japanese emotion database (original database in Figure 8), of which emotional signals were induced by self-recall experience by each subject. Database validation consists of two steps: selecting good data from the original database and evaluating the quality of the selected database. An EEG-based database validation method is proposed in this research by using the results of former sections.

## 4.1 Data Selection

With the optimal channel information, including optimal channels and the corresponding effective DWT levels, data selection was conducted as shown in Figure 8.

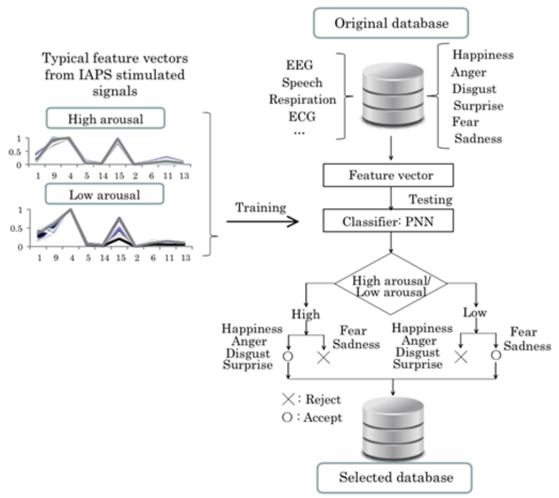


Figure 8: Procedure of data selection.

In accordance with the channel information, the typical feature vectors for both high arousal and low arousal were obtained for training the two-level PNN classifier. A similar process was also conducted on the testing EEG signals from the original database. After 0-1 normalizing and extracting a feature vector from testing EEG signals, the feature vector was input to the PNN. Based on the distribution of emotions in A-V space, six emotions could be classified into two arousal levels. If the classification results of PNN met the arousal level of A-V space, the signal was believed to be good and was accepted for constructing the selected database. By applying this selection method, about half of the data were accepted to the selected database from the original database.

## 4.2 Evaluation of Database Quality

The two-level arousal recognition method was used for evaluating the quality of the selected database. 360 pieces of signals, 60 for each emotion, were selected randomly from the original database to be used as testing signals. Another 900 pieces of signals were selected separately from the original database and the selected database to train the PNN classifier. As the first step in processing those signals, EEG signals recorded in five common channels (Fp1, C3, O1, O2, and P4) were decomposed by seven-level DWT. Then, standard deviation (SD) was extracted from each frequency component (DWT level). Using the PNN as a classifier, the recognition accuracy for each emotion was collected as the evaluation results (Figure 9).

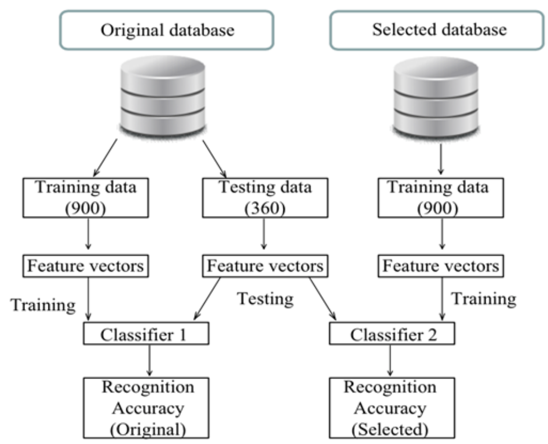


Figure 9: Procedure of database evaluation.

To reduce the effect of bias selection of data, the procedure illustrated in Figure 9 has been repeated ten times, and the average results were calculated and shown in Figure 10.

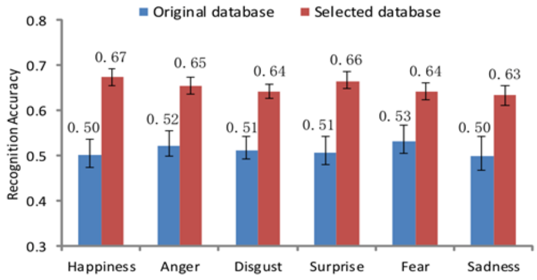


Figure 10: Recognition accuracies using original and selected databases.

The recognition accuracy can be regarded as reflecting the quality of the corresponding training database. As shown in Figure 10, a great difference in two-level arousal recognition performance appears among these two databases. The quality of the selected database is obviously higher than that of the original database. Such a result also proves that the EEG-based data selection method is an effective way to improve the quality of an emotion database.

## 5 CONCLUSION AND FUTURE PERSPECTIVES

In this research, we carried out arousal-related studies on EEG signals because they are an important area of affective computing. Firstly, by applying a cross-level feature selection method and the optimal channel groups, the recognition accuracy for two-level arousal recognition has been improved to 95.4%, which is better than the results from the full channel test. Adoption of the optimal channel groups shows that the individual difference in EEG signals is very large.

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%. The 5-channel group provides some ideas for further study on arousal-related sensitive channels.

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

However, there are still some points that need to be studied:

1. Other arousal-related features. In this research, four kinds of statistical features for detecting arousal status were discussed. However, there are still other features that we did not mention.
2. For common channels, 5 channels are simply selected out of 16 channels. However, the other channel combinations were not studied.

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