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Conference Paper · January 2011

Source: DBLP

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A FRACTAL-BASED ALGORITHM OF EMOTION RECOGNITION FROM EEG USING AROUSAL-VALENCE MODEL

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Keywords: EEG, fractal dimension, SVM, emotion recognition, music stimuli.

Abstract: Emotion recognition from EEG could be used in many applications as it allows us to know the "inner" emotion regardless of the human facial expression, behaviour, or verbal communication. In this paper, we proposed and described a novel fractal dimension (FD) based emotion recognition algorithm using an Arousal-Valence emotion model. FD values calculated from the EEG signal recorded from the corresponding brain lobes are mapped to the 2D emotion model. The proposed algorithm allows us to recognize emotions that could be defined by arousal and valence levels. Only 3 electrodes are needed for the emotions recognition. Higuchi and box-counting algorithms were used for the EEG analysis and comparison. Support Vector Machine classifier was applied for arousal and valence levels recognition. The proposed method is a subject dependent one. Experiments with music and sound stimuli to induce human emotions were realized. Sound clips from the International Affective Digitized Sounds (IADS) database were used in the experiments.

1 INTRODUCTION

Human emotion could be created as a result of the "inner" thinking process by referring to the memory or by the brain stimuli through the human senses (visual, audio, tactile, odor, taste, etc). Algorithms of the "inner" emotion recognition from EEG signals could be used in medical applications, EEG-based games, or even in a marketing study. There are different emotion classifications proposed by researchers. We follow the two-dimensional Arousal-Valence model (Russell, 1979). The two properties of this model are defined as follows. The valence level represents a quality of the emotion, ranging from unpleasant to pleasant one, and the arousal level denotes a quantitative activation level, from not aroused to excited one. This model allows us the mapping of the discrete emotion labels into the Arousal-Valence coordinate system.

To evoke emotions, different stimuli could be used, for example, visual, auditory, or combined ones. They activate different areas of the brain. Our hypothesis is that an emotion has spatio-temporal location in the brain. There is no easily available benchmark database of EEG data labelled with emotions. But there are labelled databases of audio stimuli for emotion induction such as an International Affective Digitized Sounds (IADS) (Bradley and Lang, 2007) and visual stimuli – an International Affective Picture System (IAPS) (Lang et al., 2005). Thus, we proposed and carried out one experiment on the emotion induction using IADS database of the labelled audio stimuli. We also proposed and implemented an experiment with the music stimuli to induce emotions by playing music pieces, and a questionnaire was prepared for the participants to label the recorded EEG data with the corresponding emotions (Liu et al., 2010).

There are an increasing number of algorithms to recognize emotions from EEG signals. The algorithms consist from two parts: feature extraction and classification. In work (Lin et al., 2009), a short-time Fourier Transform was used for feature extraction, and Support Vector Machine approach was employed to classify the data into emotions. 82.37% accuracy was achieved to distinguish the feelings of joy, sadness, anger, and pleasure. A performance rate of 92.3% was obtained by (Bos., 2006) using a Binary Linear Fisher's Discriminant Analysis, and the emotion states such as positive/arousal, positive/calm, negative/calm and negative/arousal were differed. By applying lifting based wavelet transforms to extract features and Fuzzy C-Means clustering to do classification, sadness, happiness, disgust, and fear emotions were recognized by (Murugappan et al., 2008). Then, in (Schaaff, 2008), optimizations such as the different window sizes, band-pass filters, normalization approaches and dimensionality reduction methods were investigated, and it was achieved an increase in the accuracy from 36.3% to 62.07% by SVM after applying these optimizations. Three emotion states: pleasant, neutral, and unpleasant were distinguished. By using the Relevant Vector Machine, differentiation between happy and relaxed, relaxed and sad, happy and sad with performance rate around 90% was obtained in (Li et al., 2009).

The main objectives of such algorithms are to improve the accuracy and to recognize more emotions. As emotion recognition is a new area of research, a benchmark database of EEG signals labeled with the corresponding emotions is needed to be set up, which could be used for further research on EEG-based emotion recognition. Until now, only limited number of emotions could be recognized by available algorithms. More research could be done to recognize different types of emotions. Additionally, less electrodes could be used for emotion recognition.

In this paper, we proposed a novel fractal based approach that allows us to recognize emotions using fractal dimension (FD) values of EEG signals recorded from the corresponding lobes of the brain. Our approach allows us to recognize emotions such as negative high aroused, positive high aroused, negative low aroused, and positive low aroused using only 3 electrodes with high accuracy. To classify emotions, we use a Support Vector Machine (SVM) implementation.

The outline of the paper is as follows. First, we describe a fractal dimension model and algorithms that we use for the feature extraction and SVM that we apply for arousal and valence levels classifications. Then, we briefly describe our experiments on the emotion inductions with audio stimuli, the algorithm implementation, and data analysis.

2 RELATED WORK

2.1 Fractal Dimension Model

As an EEG signal is nonlinear and chaotic, fractal dimension model can be applied in EEG data analysis (Pradhan and Narayana Dutt, 1993, Lutzenberger et al., 1992, Kulish et al., 2006a, Kulish et al., 2006b). For example, to distinguish between positive and negative emotions, dimensional complexity could be used (Aftanas et al., 1998). The concentration level of the subjects can be detected by the value of fractal dimension (Wang et al., 2010). Experiments on emotion induction by music stimuli were proposed, and the EEG data were analyzed with fractal dimension based approach in (Sourina et al., 2009a; Sourina et al., 2009b). A real-time emotion recognition algorithm was developed by using fractal dimension based algorithm in (Liu et al., 2010).

In our approach, we applied two fractal dimension algorithms for feature extraction, namely Higuchi (Higuchi, 1988) and Box-counting (Falconer, 2003) algorithms as follows.

2.1.1 Higuchi Algorithm

The Higuchi algorithm calculates fractal dimension value of time-series data.

$X(1), X(2), \ldots, X(N)$ is a finite set of time series samples.

Then, newly constructed time series is defined as follows:

$$X_k^m : X(m), X(m+k), \ldots, X\left(m + \left[\frac{N-m}{k}\right] \cdot k\right)$$
$$(m = 1, 2, \ldots, k) \tag{1}$$

where m is the initial time and k is the interval time.

For example, if $k = 3$ and $\mathrm{N} = 50$, the newly constructed time series are:
$X_3^1 : X(1), X(4), \ldots, X(49), X_3^2 : X(2), X(5), \ldots, X(50)$,
$X_3^3 : X(3), X(6), \ldots, X(48)$.

k sets of $L_m(k)$ are calculated as follows:

$$L_m(k) = \frac{\left\{ \left(\sum_{i=1}^{\left[\frac{N-m}{k}\right]} \left| X(m+ik) - X(m+(i-1)\cdot k) \right| \right) \frac{N-1}{\left[\frac{N-m}{k}\right] \cdot k} \right\}}{k} \tag{2}$$

where $\langle L(k) \rangle$ denotes the average value of $L_m(k)$, and a relationship exists as follows:

$$\langle L(k) \rangle \propto k^{-D} \tag{3}$$

Then, the fractal dimension can be obtained by logarithmic plotting between different k and its associated $\langle L(k) \rangle$.

2.1.2 Box-counting Algorithm

Box-counting algorithm is a popular fractal dimension calculation algorithm as its mathematical calculation and empirical estimation is straight forward (Falconer, 2003).

Let F be a non-empty bounded subset of R^n.

Then, the box-counting dimension of F is calculated by

$$\dim_B F = \frac{\log N_\delta(F)}{-\log \delta} \tag{4}$$

where $N_\delta(F)$ is the number of δ-mesh cubes that can cover F.

2.2 Support Vector Machine

The idea of Support Vector Machine (SVM) to bind the expected risk is to minimize the confidence interval while leave the empirical risk fixed (Vapnik, 2000). The goal of SVM is to find a hyperplane (Cristianini and Shawe-Taylor, 2000). There are different types of kernels. Polynomial kernel (Petrantonakis and Hadjileontiadis, 2010) used in our work is defined as

$$K(x \cdot z) = (x^T \cdot \mathrm{z}+1)^d \ . \tag{5}$$

where $x, z \in \mathrm{R}^n$ and d denotes the order of the polynomial kernel.

3 EXPRIMENT

We use EEG data sets labelled with emotions collected in the experiments on emotions induction with audio stimuli and described in our previous work (Liu et al., 2010). Two experiments were carried out to elicit the emotions: negative high aroused (fear), positive high aroused (happy), negative low aroused (sad), and positive low aroused (pleasant) with different audio stimuli. The first experiment used music pieces labelled by other subjects with emotions using a questioner. The second experiment used sound clips labelled with emotions from the International Affective Digitized Sounds (IADS) database. The music experiment collected EEG data from 10 subjects, and the IADS experiment collected EEG data from 12 participants. In the music and IADS experiments, an Emotiv device with 14 electrodes located at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4 according to the American Electroencephalographic Society Standard was used. The sampling rate of the device is 128Hz. The bandwidth of Emotiv is 0.2-45Hz, digital notch filters are at 50Hz and 60Hz; and A/D converter is with 16 bits resolution. After the study on the channels choice, 3 channels such as AF3, F4 and FC6 were used for the recognition tasks.

4 IMPLEMENTATION

4.1 Pre-processing

The collected data was filtered by a 2-42 Hz bandpass filter since the alpha, theta, beta, delta, and gamma waves of EEG lie in this band (Sanei and Chambers, 2007).

4.2 Features Extraction

The FD values were used to form the features as follows. For arousal level recognition, one electrode FC6 corresponding to the different excited brain state levels of subjects was finally chosen to form the fractal dimension feature:

$$Feature_{FD}^{Arousal} = [FD^{FC6}] \tag{6}$$

In previous works (Jones and Fox, 1992, Canli et al., 1998), it was shown that the left hemisphere was more active during positive emotions, and the right hemisphere was more active during negative emotions. We proposed to compute FD values from EEG signals recorded from the left and right hemispheres for valence recognition. Our hypothesis is that the FD values from both hemispheres could be used in valence classification. To test our hypothesis, we collected data from AF3 electrode which is located on left hemisphere and from F4 electrode which is located on the right hemisphere. The valence features was defined as follows:

$$Feature_{FD}^{Valence} = [FD^{AF3}, FD^{F4}] \quad (7)$$

where FD^{AF3}, FD^{F4} denotes the FD values computed from EEG signal recorded from AF3 and F4.

Since there are individual differences in emotion processing by brain (Hamann and Canli, 2004), we proposed a subject dependent approach. We proposed a sliding window with the size of 1024 and 99% overlapping of the sampled data to calculate fractal dimension (FD) values with Higuchi and Box-counting algorithms to set up the training and testing data for SVM classifier. For example, for FD^{FC6}, a set of FD values was computed with the sliding window: $FD_1^{FC6};\ldots;FD_n^{FC6}$. The total number n of FD values depends on the input data size and the sliding window used.

4.3 Support Vector Machine Classification

Although we have only one feature for arousal level recognition and two features for valence level recognition respectively, the SVM kernel can project low dimension feature into higher dimension space to search for the hyperplane (Noble, 2006) which can differentiate two classes, namely high arousal and low arousal levels with the arousal feature, and positive and negative levels with valence features. The MATLAB R2010a Bioinfo Toolbox was used. The order of SVM polynomial kernel was set to 5. For the arousal level recognition, FD values of high arousal level with negative and positive valence levels, and low arousal level with negative and positive valence levels were put together with the labels. For the valence level recognition, the FD values FD^{AF3}, FD^{F4} of positive valence level with high and low arousal level, and negative valence level with high and low arousal level were put together with the labels. For both arousal and valence level recognition, 50% of these data were randomly selected and fed into the SVM classifier as training data, and the other 50% were used as testing data. 50 iterations were executed to get the mean accuracy $\bar{A}$.

5 RESULTS AND ANALYSIS

The classification accuracy comparison is shown in Figure 1 and 2 for arousal level recognition in the music and IADS experiments correspondingly. In Figure 3 and 4, the accuracy for valence level recognition in the music and IADS experiments is shown. The vertical axis denotes the value of $\bar{A}$. The horizontal axis represents different subjects. Since we ignored the data of experiments when the targeted emotion was not induced as expected which was recorded in the subject's questioner answer, for arousal level analysis, data of subjects 1, 2, 3, 4, 5, 6, 7, 9, and 10 from the music experiment, and data of subjects 1, 2, 3, 4, 5, 6, 9, 10, and 11 from the IADS experiment were used. For the valence level analysis, data of subjects 1, 3, 4, 5, 7, 8, 9, and 10 from the music experiment, and data of subjects 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11 and 12 from the IADS experiment were used. The dash line with the diamonds denotes the performance of our algorithm with Higuchi method, and the line with the squares denotes the performance of our algorithm with box-counting method. When comparing these two algorithms, we can see that the performance of our algorithm based on Box-counting and Higuchi is almost breakeven: Higuchi outperforms box-counting algorithm for 4 subjects out of 9 in the arousal level recognition for both IADS and music experiments, for 5 out of 8 subjects in the valence level recognition for the music experiment, and 7 out of 12 subjects in the valence recognition for IADS experiment.

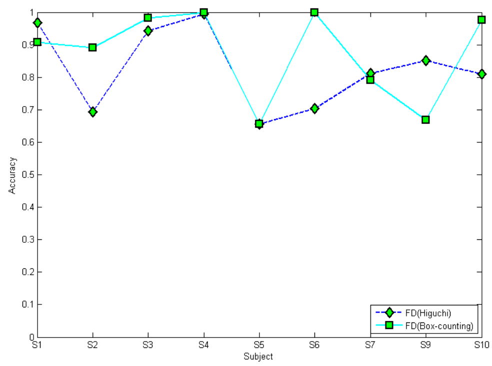

Figure 1: Comparison of arousal levels recognition accuracy for the music experiment

In our algorithm, we used only 3 electrodes to recognize emotions, and by combining the two dimension arousal and valence, we can get the recognition of emotions that can be mapped to the 2D Arousal-Valence model. In (Zhang and Lee, 2009), positive and negative valence levels were recognized, and the accuracy of 73.00% was obtained. Positive, negative, and neutral were differentiated, and the accuracy of 72% was obtained in (Schuster et al., 2010). Our work identified not only the valence but also the arousal levels and has got a higher accuracy (the maximum accuracy 100%, and the worst performance is around 70%).

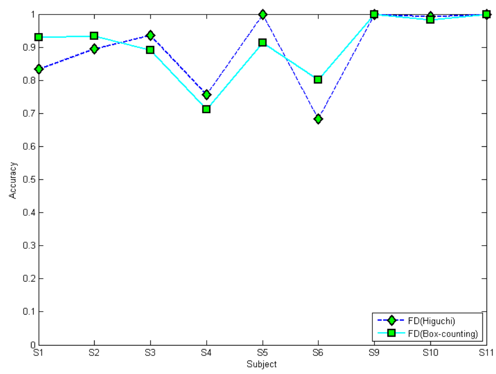

Figure 2: Comparison of arousal levels recognition accuracy for the IADS experiment

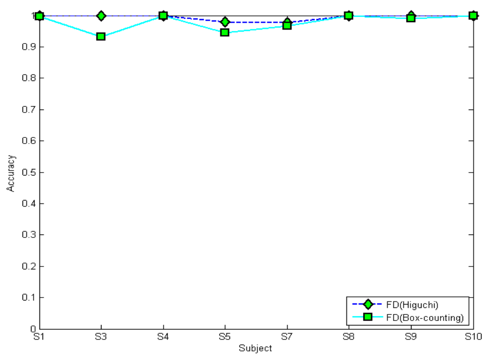

Figure 3: Comparison of valence levels recognition accuracy for the music experiment

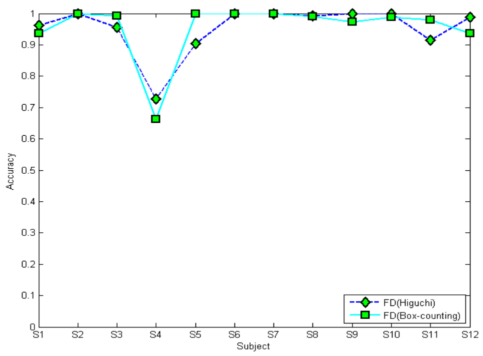

Figure 4: Comparison of valence levels recognition accuracy for the IADS experiment

In another work (Chanel et al., 2006), 64 channels were used. Different EEG frequency bands associated with different electrodes locations were used for features extraction, and two classifiers such as Bayes and Fisher Discriminant Analysis were compared. Finally, the best accuracy result of 58% was achieved to distinguish three arousal levels using four subjects' data. Our algorithm outperforms the above algorithm by using less electrodes and having the better accuracy.

6 CONCLUSION

In this paper, we proposed a novel fractal based approach for emotion recognition from EEG using 2D Arousal-Valence model. Fractal dimension features for arousal and valence levels recognition were extracted from the EEG data sets labelled with emotions for each subject. Based on the features, arousal and valence levels were classified correspondingly. Higuchi and box-counting algorithms with sliding window were implemented for FD values calculations, and the accuracy of the arousal an valence levels recognition was compared for both algorithms. The proposed method allows us to recognize emotions combined as negative high aroused (fear), positive high aroused (happy), negative low aroused (sad), and positive low aroused (pleasant) states using only 3 electrodes with high accuracy. This study is a part of the project EmoDEx described in http://www3.ntu.edu.sg/home/eosourina/CHCILab/projects.html

ACKNOWLEDGEMENTS

This project is supported by grant NRF2008IDM-IDM004-020 "Emotion-based personalized digital media experience in Co-Spaces" of National Research Fund of Singapore.

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