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Detrended Fluctuation Analysis Based on the Affective ECG

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Abstract

Electrocardiography (ECG) is one of the most important physiological signals, which has been proven to contain reliable affective information. Four kinds of objective affects including happiness, sadness, angry and fear, are induced by affective fragments from movies, and ECG signals are recorded by Biopac MP 150 synchronously. In an independent experiment the affective videos are played twice, and in the second presentation the press file of affective re-evaluation is obtained, which registers the subjective experience of participants and help us intercept the reliable affective ECG. The detrended fluctuation analysis is used to quantitate the temporal correlations by the scaling exponent in affective ECG. And the result showed that ECG of happiness, sadness, angry and fear had long-range correlations. Then the scaling exponent is used by the binary classifier of Fisher as an affective feature, and the result showed that the correct recognition rate of happiness, sadness, angry and fear are 89.74%, 90.1%, 70.43%, 84.44% respectively. The whole experiment displays that the nonlinear features have a fine distinction in different emotions.

Keywords: Affective ECG; Press File of Affective Re-evaluation; Detrended Fluctuation Analysis; Scaling Exponent

1 Introduction

Affect detection is the key problem of affective computing and the basic function of harmonious human-machine interactive environment. The human's emotional states are psychological and physiological changes inherently, which are manifested by behavior, facial expressions and physical signals. By analyzing of these observable signals, the human's affective state can be inferred. Currently the research of affect detection mainly focuses on the signals such as speech, facial expression, text [1] and physiological signals [2, 3]. One advantage of monitoring physiological signals rather than the face and voice is that physiology is less susceptible to social masking. This might be particularly important for certain applications such as deception detection, interventions to treat individuals with autism, and computer-mediated social interactions (e.g., computer tutors that simulate human tutors).

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ECG is one of the most important physiological signals, which has been proven to contain reliable affective information [3-6]. Recently the main methods of these studies are extracting the ECG's statistical features on time domain or frequency domain, then using these features to build affective classification mode. In the reference [3], four kinds of physiological signals are collected by BIOPAC150, which are eleectromyogram, electrocardiogram, skin conductivity and respiration changes. A large number of physiological features from various domains, including time/frequency, geometric analysis, mutiscale entropy, etc., are proposed. Based on these features, the author can find the best emotion-relevant features, the effectiveness of which is proven by classfication results. To classify four kinds of emotions, the extended Linear Discriminant Analysis (pLDA) is performed and an improved recognition accuracy of 95% and 70% for subject-dependent and subject-independent classfication is achieved. In the reference [5], author used several peripheral physiology signals, including ECG, EMG, and GSR, to realize the automative detection of affective states. And in the paper the efficacy of affect detection using a host of feature selection and classification techniques on these three physiology signals are evaluated. The results indicated that the user-dependent modeling approach based on ECG was feasible. In the reference [6], a methods based on the empirical mode decomposition is proposed to detect the emotion status. And there are many features based on the instantaneous frequency and the local oscillations within every mode are extracted. And the results show that the feasibility to setup empirical mode decomposition and to extract frequecy feature.

From the above studies, we can find that, these studies mostly have ignored the fact that cardiac system is a typical nonlinear system and ECG has many nonlinear characteristics. Only using the statistical features without nonlinear features of ECG will decrease the detection precision obviously. So in this paper a nonlinear feature will be used by Fisher classifier to detect the four kinds of target emotions, which are happiness, sadness, angry and fear. This nonlinear feature named the scaling exponent, is calculated by the algorithm of Detrended Fluctuation Analysis (DFA) and used to reveal the long-rang and power-law correlation of non-stationary time series.

2 Theory Background and Related Work

2.1 The Affective Detection Theory Based on Physiological Signals

As early as 100 years ago, psychologist, physiologist, philosopher have studied about emotion, and they generally think that emotion is a multidimensional component which includes the subjective experiences, explicit expressions and physiological activations [7]. Awakening certain parts of nervous system will provide the energy and space for the specific emotional movements. Ascending pathway will transfer the affective stimulus from the limbic system to the brain center. When the neural impulses pervade the cerebral cortex, we will experience all kinds of emotion. At the same time descending pathway regulate the awakening degree of automatic nervous system, which will control the movements of physiological signals. Consequently the physiological signals may have the distinct activity pattern in different affective state.

In many affective theories, the hypothesis of James-Lange is particularly relevant to our research. Their theory proposes that emotions are "readouts of physiological changes in the body", and the awareness of peripherally physiological changes is emotion. That means affective stimulus occurred firstly, then peripherally physiological responses appeared, such as rapid heart beat, body shaking, constriction of blood vessels or spasm of trachea, finally some special emotion is perceived [8]. According to James-Lange's view different emotion states will correspond to different patterns of physiological activities. Despite a wide range of disputes in this point, the application of affect detection based on physiological signals has been developed widely.

2.2 Related Work in Detrended Fluctuation Analysis

ECG is one of the most typical physiological signals, which is non-stationary and nonlinear. Recently there are a lot of nonlinear algorithms used in ECG, such as the algorithm of calculating Lyapunov exponent [9], correlation dimensions [10] and approximate entropy [11]. These methods require very long and stationary data, and this condition is difficult for physiological signals. So further discussions on calculating the nonlinear features of physiological signals are still needed.

Peng [12] put forward Detrended Fluctuation Analysis (DFA), which was suitable for the non-stationary time series to investigate the long-range and power-law correlation. The method was used to detect the related degree within the DNA molecular chain firstly, then it was used widely in fields of life science [13,14], meteorology [15], hydrology [16], economics [17], etc. Recently the method was used to analyze the physiological signals, and has achieved initial success. Peng et al. [18] applied DFA to quantify the long-range correlation property in heartbeat physiological time series, and studies reveal that the beat-to-beat fluctuations in heart rate of normal person display the kind of long-range correlation, but the heart rate time series from patients with severe congestive heart failure breakdown this long-range correlation behavior. And DFA used in heartbeat physiological time series may distinguish healthy from pathologic data sets based on differences in these scaling properties. Lee et al. [19] used DFA to analyze the sleep ECG, and concluded that the different sleep state had different average scale indexes. Parish et al. [20] used DFA to analyse the energy fluctuations in human hippocampus and showed that the long-range temporal correlations with power-law scaling, and that these correlations differ in epileptogenic and non-epileptogenic hippocampus. Bhattacharya J. et al. [21] had investigated the nature of spontaneous fluctuations of single neurons from human hippocampus-amygdale by DFA and Multi-scale Entropy (MSE). Both the analysis displayed that the presence of long-range power-law correlation over time in the inter-spike-intervals sequences. Cai Shi-Min et al. [22] applied the DFA to investigate the scaling behavior of stride interval fluctuations of human gait. The analysis showed that the scaling behaviors of the stride interval of a human walking at normal, slow, and fast rate are similar and the long-range correlations are observed during the spontaneous walking by removal of the trend in the time series. Nikulin V.V. and Brismar T. [23] study temporal correlations in electroencephalographic (EEG) neuronal oscillations, which were characterized with respect to their topography, frequency-band specificity (α and β oscillations), gender and age. Using DFA, the topography of long-range temporal correlations was comparable for α and β oscillations, showing largest scaling exponents in the occipital and parietal areas. Long-range temporal correlations were stronger in α than β oscillations. In both frequency bands, long-range temporal correlations were stronger in males than in females and the long-range temporal correlations were largely unaffected by the age of the subjects.

3 Acquisition and Preprocessing of Data

3.1 Experimental Schema

How to design the experimental schema will be related with the following acquisition and analysis of affective physiological signals. So when designing the schemas, we must consider these following questions: 1) How to elicit emotions, in laboratory or in real life environment? 2) Which kinds of affective inducing materials will be used? 3) Which target emotion will be elicited? 4) How to choose the participants?

In order to facilitate the acquisition of ECG signal, we decided to elicit affect in laboratory environments. And there are many materials to elicit the participants' emotion, such as pictures (IAPS) [24], music [3], and a human-computer interaction process [5]. In order to evoke the enough intensity of affective ECG, we decide to use the movie clips as the affective inducing materials. The target emotions evoked in our experiments include happiness, sadness, angry, and fear. And Biopac MP 150 is used to collect the multi-channel physiological signals. Fig. 1 has displayed the acquisition process of affective data. A total of 300 students take part in the experiment, and they all need to fill the informed consent table. And Biopac MP 150 is used to collect the participants' physiological signals.

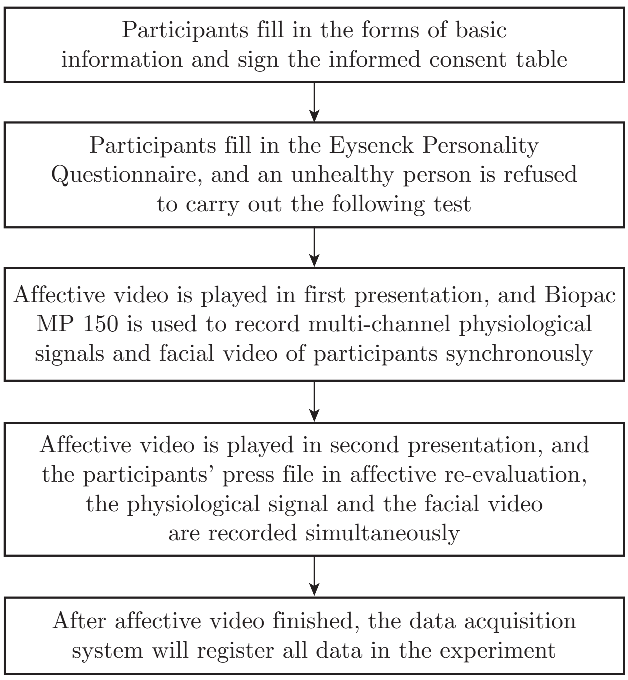

Fig. 1: The process of data acquisition

In an independent experiment one movie clip will be played twice, accordingly only one target emotion will be inspired. In the first presentation of affective inducing video, the participants are asked to watch the video and taste the target emotion carefully, and their ECG is collected synchronously. In the second presentation the participants' affective experiences are collected by the participants' press file. Fig. 2 displays the arrangements of four kinds of affective movie clips.

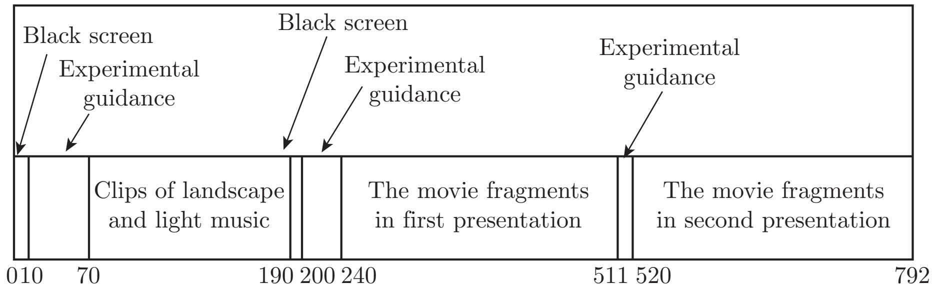

Fig. 2: The arrangement of affective movie clips

3.2 The Press Files of Affective Experience

In the process of data collection, we also use the press file to record the affective experience of participants. This press file is a *.txt file, which include the '01' string showed the affective experience of participants. '0' denotes that the participants don't taste the target emotion, and '1' denotes the participants do taste the target emotion. In the second presentation of affective video, participants are asked to recall the affective experience in the first presentation, and press the button when they recall the target affect, and then the character of '1' is recorded in the press file. So the successive sequences of '1' reveala the lasting duration of target emotion experienced by participants, the timescale of the successive sequences of '1' can be used as the foundations of cutting affective ECG.

We count all valid press file of affective experience, and gain the distributions of press in four kinds of target emotion, as shown in Fig. 3. In these figures the horizontal axis represents the timescale of affective videos, and the vertical axis represents the number of participants who press the button at that time point. In the happy video most of participants press the button in 280 s, 338 s, 378 s and 398 s, so in these time points happiness has been inspired greatly. In the grief video many participants press the button in 640 s$\sim$800 s, in which the time point of sadness has been inspired mostly. In the angry video most participants respond to the angry affect in 290 s$\sim$300 s, 460 s$\sim$500 s. And in the fear video most participants experiance the fear affect in 320 s$\sim$370 s, 410 s$\sim$460 s.

3.3 Preprocessing of Affective ECG

In the process of experiment we collect many participants' original ECG, but a part of them is valid. The proportion of all kinds of data is displayed in Table 1.

Table 1: Proportion of all kinds of data

Affect Type	The total number of ECG	Number of valid data	Number of invalid data
Happiness	132	94	38
Sadness	102	80	22
Angry	72	47	25
Fear	62	45	17

After deletion of the invalid data, we need to intercept the ECG signal related with participants'

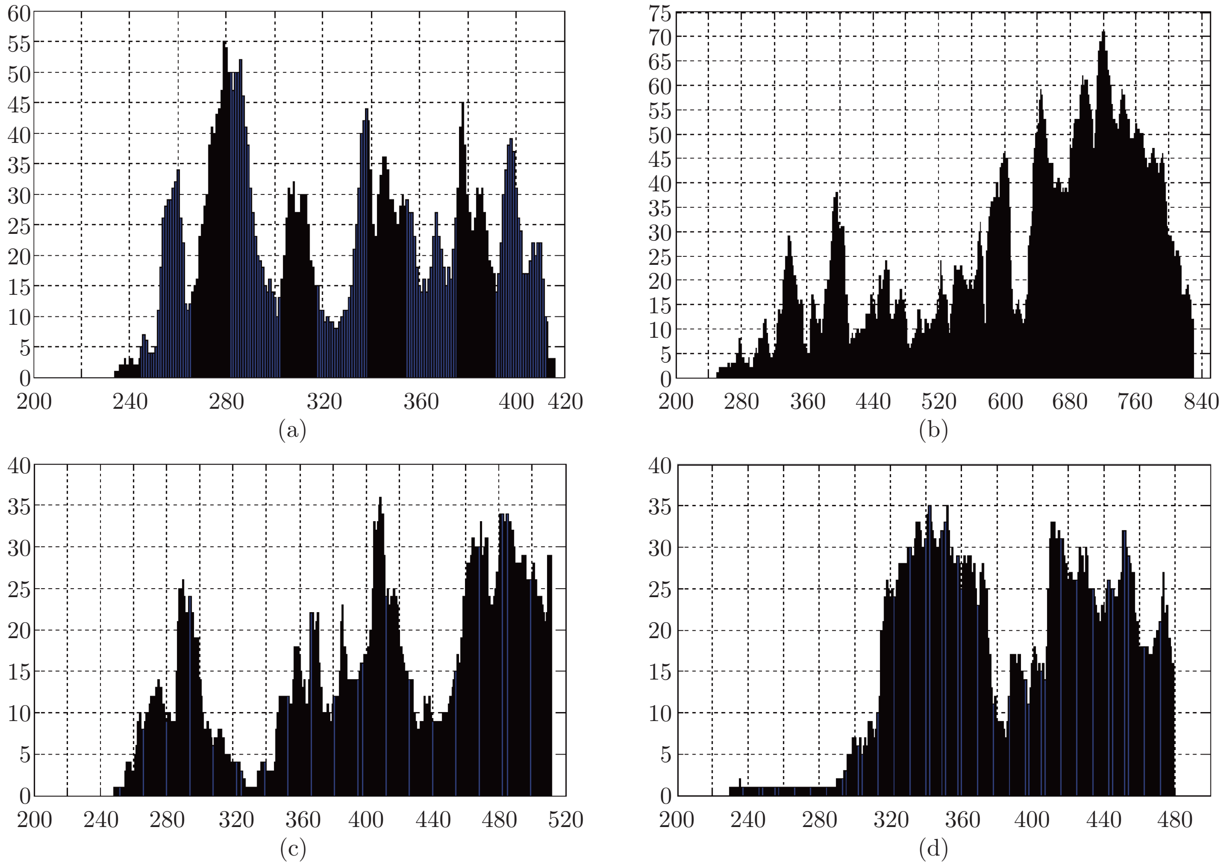

Fig. 3: (a) The distribution of press in happiness; (b) The distribution of press in sadness; (c) The distribution of press in angry; (d) The distribution of press in fear

target affective experience. In order to position the start time point of target affect emergence, we devise the press file of affective experience, in which the successive '1' sequence is corresponded to the duration of affective experience. Searching the longest '1' sequence, calculating the start time and the end time of the longest '1' string, and based on the start time we cut an ECG signal that lasted for 60s as the affective ECG. Fig. 4 displays the affective ECG intercepted.

For the original affective ECG, there are lots of noises, such as power line interference from electric system, drifting baseline from the breathing of participants, etc. By setting 35 HZ low pass filter and 50 HZ trap filter in Biopac MP 150, we can get rid of most of the power line

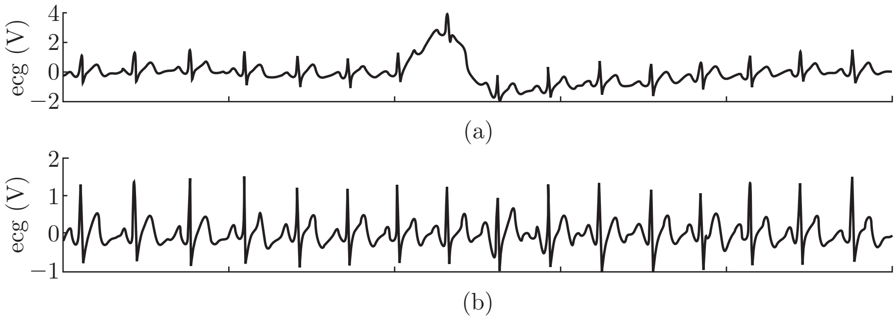

Fig. 4: The affective ECG signals

interference, myoelectricity interference and electromagnetic interference. By decomposition and reconstruction of wavelets we can remove the drifting baseline. Fig. 4 reveals the affective ECG after eliminating the noises.

Further ECG will be normalized to make the signal's value between 0 and 1. The formula of normalization is:

$$ecg\_normalized = \frac{ecg - ecg\_\min}{ecg\_\max - ecg\_\min} \tag{1}$$

4 Detrended Fluctuation Analysis in Affective ECG

Detrended Fluctuation Analysis (DFA) is a kind of data analysis method, which can discover and quantify scale-dependent properties in complex systems, and has been applied to detect Long-range Temporal Correlations (LRTC) in noisy non-stationary signals. DFA was firstly developed to describe the correlation properties in DNA nucleotides [10], and later was extended to heartbeat time series [16]. Nowadays DFA has been used in biological systems widely. In our study, we closely follow the method of Peng.

4.1 The Algorithm of DFA

Firstly for a time series $\{x_i\}$ ($i = 1, 2, \cdots$, N), the mean of $\{x_i\}$ is subtracted, and the sequence of $y(k)$ is got:

$$y(k) = \sum_{i=1}^{k}(x_i - < x >), \quad 1 \le k \le N \tag{2}$$

Then we divide the sequence $\{y(k)\}$ into N_s non-overlap segments V_j ($j = 1, 2, \cdots, N_s$), where $N_s = \text{int}(N/s)$ and s represents the length of the segments.

Secondly for each of these segments V_j ($j = 1, 2, \cdots, N_s$), the local trend $P_j^m(k)$ is calculated:

$$P_j^m(k) = a_{jo} + a_{j1}k + \cdots + a_{jm-1}k^{m-1} + a_{jm}k^m \tag{3}$$

where k is the point in V_j. Then the accumulated deviation in every segment is computed:

$$F^2(j, s) = \frac{1}{s}\sum_{i=1}^{s}\{y[(j-1)s + i)] - P_j^m(i)\}^2, \quad j = 1, 2, \cdots, N_s \tag{4}$$

Finally, the root-mean-square of fluctuation in every segment is computed, which is the fluctuant function F(s):

$$F(s) = \Big[\frac{1}{N_s}\sum_{j=1}^{N_s} F^2(j,\ s)\Big]^{1/2} \tag{5}$$

In the formula (5), F(s) is the function of s, and we can plot the logarithmic graph of $Log(F(s)) - Log(n)$, and the slope of the curve is the scaling exponent ∂. And $F(s)$ and s satisfies the following formula:

$$F(s) \propto s^{\partial} \tag{6}$$

The scaling exponent ∂ provides a quantitative measure of the temporal correlations in the time series $\{x_i\}$. If the signal is completely uncorrelated, the scaling exponent will satisfy $\partial = 0.5$. If $\partial \neq 0.5$ means the time series has the nature of long-range and power-law correlations. IF $0.5 < \partial < 1$, the data are correlated as that large fluctuations are likely to be followed by large scaling exponent and vice versa. If $0 < \partial < 0.5$, the time series has "anti-correlated" characteristic that large fluctuations are likely to be followed by small scaling exponent and vice versa. As the scaling exponent increases from $\partial = 0.5$ toward $\partial = 1$, the temporal correlations in the time series decay much slowly with time. However, when $\partial > 1$, the correlations no longer exhibit power-law behavior and decay more rapidly with increasing ∂. A special case of $\partial = 1$ corresponds to 1/f noise. A large scaling exponent re?ects slow fluctuations and a small scaling exponent reflects more rapid fluctuations.

4.2 Experimental Results

Fig. 5 displays the experimental results used in DFA in four kinds of affective ECG.Means and standard deviations of four kinds of target affects are displayed in Table 2. The means of happiness's scaling exponent is 0.4754, which is minimal; the means of sadness is 1.2315, which is maximal; the means of angry and fear is 0.7231 and 0.9526 respectively. These results illuminate that the ECG of happiness exhibit anti-correlated behavior, which means the bigger scaling exponent response to the smaller fluctuations; In ECG of sadness the correlations exhibit long-range but on power-law behavior. And in the ECG of angry and fear there are persistently long-range and power-law correlations.

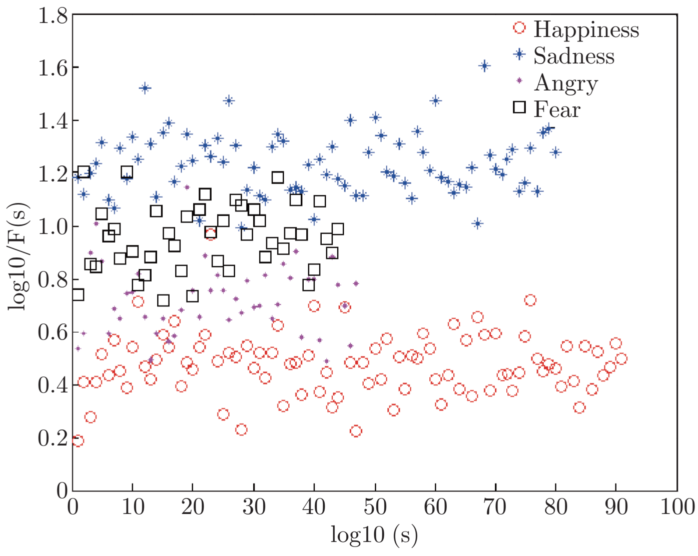

Fig. 5: The distribution of in four kinds of affect

4.3 Classification Based on the Scaling Exponent

The scaling exponent ∂ is used as affective feature, and Fisher is used as classifier, we can finish the detection of four kinds of target affect. In order to reduce the complexity, we regard the multiple classifications as a binary classification, which means we can suppose one kind of affect

Table 2: The means and standard deviations of four kinds affects

Affective Type	The means of ∂	Standard deviations of ∂
Happiness	0.4754	0.1198
Sadness	1.2315	2.6813×10^{-15}
Angry	0.7231	4.4889×10^{-16}
Fear	0.9526	2.9653×10^{-15}

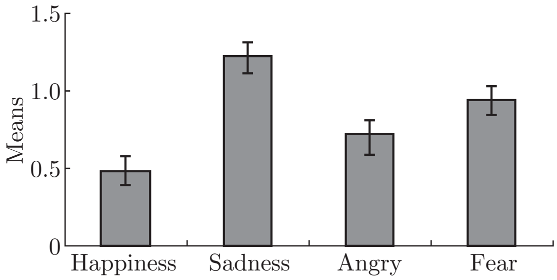

Fig. 6: The means of ∂ in four kinds of affect

as target affect and other kinds of affects as interferential affect. True Positive Rate (TPR) and False Positive Rate (FPR) [24] are used to evaluate the effect of classifier. The greater TPR means the higher correct recognition rate and the better effect of classification, the smaller FPR means lower error recognition rates and the better effect of classification.

The scaling exponent of DFA in four kinds of affects are treated as sample data, in which 60% data are used as training data to train the Fisher, and the remaining data are used as test data to check the performance of classification model. And finally TPR and FPR of four kinds of target effect are calculated and showed in Table 3.

Table 3: TPR and FPR of four kinds of affects

Affect Type	TPR	FPR
Happiness	0.8956	0.0058
Sadness	0.9010	0.0162
Angry	0.7043	0.0837
Fear	0.8444	0.0826

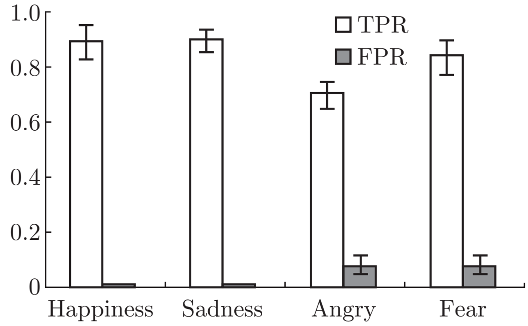

Fig. 7: The TPR and FPR of four kinds of affect

From Table 3 we can find that the classification model based on the scaling exponent is appreciable. And the correct recognition rate of happiness, sadness, angry and fear are 89.74%, 90.1%, 70.43%, 84.44% respectively, the error recognition rates of happiness, sadness, angry and fear are 0.58%, 1.62%, 8.37%, and 8.26% respectively. These errors may be caused by feature selection. We should extract more nonlinear features to improve classification accuracy.

5 Summary and Discussion

In the paper an experimental schema is designed to collect ECG signals in four kinds of affective status. The affective inducing material is adopted movie clips and the four kinds of target emotions are happiness, sadness, angry and fear. 300 freshmen in Southwest University take part in the experiment. In an independent test, the movie clips will be played twice. In the first presentation we mainly collect the ECG signals, and in the second presentation we mainly obtain the press file of affective experience, which is a txt file record the '01' string. The successive sequence of '1' in this file means a lasting duration of target emotion experienced by participants. We calculate the start time point of the longest sequence of '1', and accordingly intercept 60s ECG signals as the affective ECG. After denoising and normalization of the affective ECG, Detrended Fluctuation Analysis (DFA) is used to calculate the scaling exponent which reflects the long-range and power-law correlation. And the result shows that the ECG of happiness exhibit anti-correlated behavior, the ECG of sadness has long-range but no power-law correlation, the ECG of angry and fear is persistently long-range and power-scale correlation. Then we use the scaling exponent as the affective feature and Fisher as the classifier to realize affect detection, and the result shows the correct recognition rate of happiness, sadness, angry and fear is 89.74%, 90.1%, 70.43%, 84.44% respectively. So the model of affect detection based on the scale indexes is appropriate.

There are two innovative points in this paper. Firstly we design an experiment scheme which can obtain the subjective emotion experience of participants by the press file. Comparing with other experimental schema, the advantage of our experiment is that we adopt recalling method to gather the participants' subjective experiments, which are recorded in the press file. Based on this file affective ECG can be intercepted exactly. Secondly the algorithm of DFA is used to calculate a nonlinear property (the scaling exponent) of affective ECG, and we use this nonlinear property as the affective features to realize the affect detection. We can find that it is feasible and can perform well to use nonlinear property as an affective feature.

There are a lot of research work in the future, mainly in the following aspects: 1) Enlargement of the experimental data, especially the data of angry and fear; 2) Study the other nonlinear features of ECG, such as the index of Lyapunov, approximate entropy and correlation dimension; 3) Select the combinations of optimal features based on statistical features and nonlinear features; 4) Apply and compare various classifiers, such as Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Linear Discriminate Analysis (LDA), etc. 5) Build the use-independent model based on the optimal feature combinations and the optimal classifier.

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