Research of Emotion Recognition Based on Pulse Signal

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***Abstract*—As one of the most important human physiological signals, pulse signal contains a wealth of information which can reflect the change of emotions. In this paper, time-domain features and wavelet coefficient features through wavelet transform are extracted respectively from raw pulse signals. Then the improved Max-Min Ant System (IMMAS) combined with Fisher classifier is used for feature selection and the classification of happiness, disgust, grief, anger, fear. Finally, not only good recognition effect, but also some useful feature combinations are obtained.**

Keywords- pulse signal; emotion recognition; wavelet transform; IMMAS

I. INTRODUCTION

Affective computing has become one of the hottest issues in advanced human-computer interaction (HCI) today. Emotion recognition is one of the important parts of affective computing, and the research contents include facial expressions, speech tone, body postures, text and physiological signals, etc [1]. Compared with facial expressions and speech, application of physiological signals in emotion recognition has been paid little attention so far [2].

Through experiments, Ekman et al. concluded: at least for some emotions, the physiological responses are specific, so emotion states could be recognized through extracting features of physiological signals [3]. Pulse is a significant physiological signal of human body, and the research of it is not only an ancient subject, but also an important subject that modern science must face, and little research has been done in the field of pulse signal-based emotion recognition. In our research, firstly, large amounts of subjects were recruited for the emotion-induced experiment, and the pulse signals under specific emotional states were collected. Then using the ability of wavelet transform who can effectively extract signal details, we calculated 104 features from domains of time and wavelet. After that, IMMAS combined with Fisher was used for feature selection and classification of the six emotions (happiness, surprise, disgust, grief, anger, fear), and the recognition rate reached 75.36 %, 81.48%,74.67%, 87.88%, 75.89%, 81.43%, respectively. Finally, while guaranteed the recognition effect, we limited the dimensions of feature subsets in the process of feature selection, and feature subsets with lower dimensions which can effectively classify the emotions are obtained.

II. DATA COLLECTION

The physiological signals were recorded using MP150 from Biopac Systems Inc (Goleta, USA). The subjects were all freshmen with good health, aged from 19 to 25, and had no history of mental illness. The experimental materials were emotion-rich movie clips with high social accreditation. Before the experiment, the subject was required to fill in personal information, consent agreement of voluntary testing and alexithymia questionnaire. During the experiment, a camera with high resolution was used to record the condition of the subject, and the experimenter marked the collected pulse signal in visual interface of MP system. At the end of each movie clips, the subjects would fill in an emotion questionnaire which reflected the state and the intensity of emotion elicited by the video. According to the markers and the emotion questionnaire, we choose 242 groups of effective pulse signals for analysis.

III. EFEATURE EXTRATION OF PULSE SIGNAL

A. Introduction of Pulse Waveform

A standard pulse waveform is shown in Figure. 1.

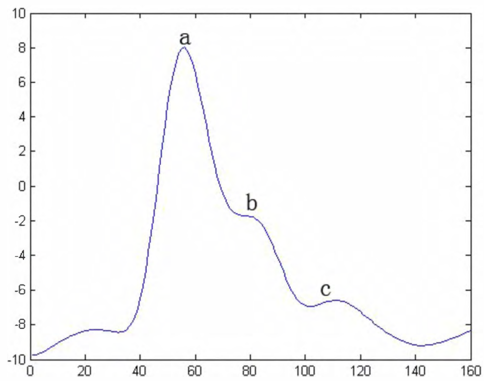

Figure 1. Pulse waveform

a, b and c in Fig. 1 represent percussion wave, tidal wave, dicrotic wave, respectively. Generally speaking, percussion wave is the highest peak in a pulse waveform, and it also reflects the maximal values of arterial pressure and volume.

The changes of percussion wave can reflect the changes of physiological factors [4].

Tidal waves and dicrotic waves of different people vary greatly because of age and health states, and they are usually not obvious and difficult to detect. Thus we extracted mainly the features of percussion wave and pulse signal for analysis, and proved that there contains numerous emotional information in pulse signal.

B. Discrete Wavelet Transform

The continuous wavelet transform is defined as

$$WT_f(a,\tau)=\frac{1}{\sqrt{a}}\int_R f(t)\psi^*(\frac{t-\tau}{a})dt, \quad (1)$$

where $\psi(t)$ is the basic wavelet function, superscript * represents conjugation; a,τ denote scale and translation parameters, respectively($a,\tau\in R$ and $a>0$). The wavelet transform of signal means the signal is projected onto the two dimensional time-scale phase plane, which will help extract some essential features of the signal. Discrete wavelet transform is to discretize a,τ . The discretized wavelet basis function satisfies the completeness condition, the transformed wavelet coefficient has no redundancy, the data are compressed, and the computational complexity is reduced.

C. Percussion Wave Crest Detection Based on Wavelet Transform

The signal duration is 80 seconds, with 16000 data points, and we denote the original signal as S. Use Coiflet 1 wavelet to decompose the original signal into three layers, and then reconstruct the high-frequency coefficients of the third layer [4],[5]. The reconstructed signal is denoted as D3. Figure 1 describes the process of main wave crest detection. And points needed to be detected is marked by *.

Step1: Divide D3 into 64 time slices, each time slice contains 250 data points, namely the duration is 1.25 seconds. In every slice, the threshold is set as the sum of mean and variance of D3. Find out all the extreme points whose value is larger than the adaptive threshold (see Figure. 2a).

Step 2: Mark the corresponding points found by Step 1 in the original signal S (see Figure.2b).

Step 3: Find the maximum point in each small area through local search, and the percussion wave peaks are near these maxima (see Figure.2c).

Step 4: Through searching the vicinities of the points determined by Step 3, accurately position the percussion wave peaks (see Figure. 2d).

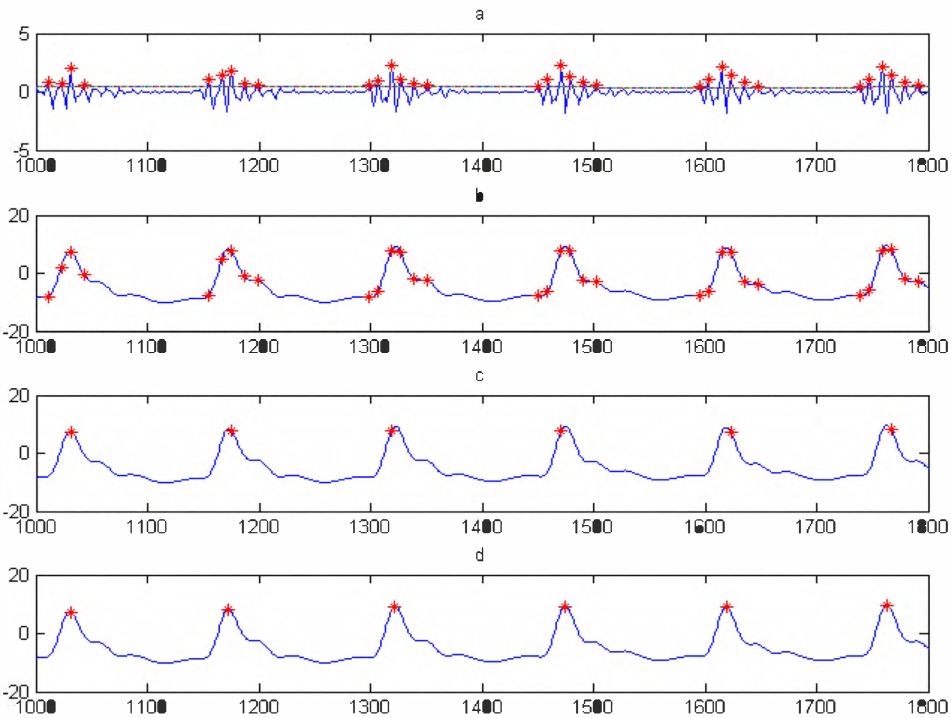

Figure 2. Process of percussion wave crest detection

D. Feature Extraction of Pulse Signal

After positioning the main wave peaks, we extracted 20 time domain features: maximum, minimum, mean, median, standard deviation of the main wave peak; maximum, minimum, mean, median, standard deviation of the first difference of the main wave peak; minimum, mean, median, standard deviation of the pulse signal. At the same time, we do 7-layers wavelet decomposition on pulse signal, and extract maximum, minimum, mean, standard deviation, median, quadratic sum of each layer's low frequency and high frequency coefficients, thus 84 wavelet coefficient features are obtained. There are a total of 104 features from domains of time and wavelet.

IV. FEATURE SELECTION

MMAS is first promoted by Stützle and Hoo through some modification of AS. In MMAS, the value range of pheromone is limited to an interval [τmin, τmax], which effectively avoids the premature convergence and increases search capability of the global optimum [6]. However, there are still some deficiencies of MMAS. For these deficiencies we improved the algorithm and IMMAS is obtained. Then IMMAS and Fisher were used for feature selection.

A. Improved Max-Min Ant System

In MMAS, since the initial pheromones on all paths are the same as τmax, and the pheromone update in each cycle happens only to the optimal solution of this cycle or the best-so-far solution, which makes the amount of pheromone on most paths the same in a long time, thus affects the search speed of the optimal solution [7]. To overcome these shortcomings, not only local search and mutation are introduced to MMAS, meanwhile, pseudorandom proportional rule and local pheromone update rule are borrowed from ACS (ant colony system)[8]. So, while searching better solution, IMMAS can also speed up convergence.

1) Pseudorandom Proportional

Refers to ACS algorithm, ant k at node i moves to the next node j (choose the next feature j) according to pseudorandom proportional rule which is shown as following:

$$j = \begin{cases} \arg\max\limits_{l \in N_i^k} \{\tau_{il}[\eta_{il}]^{\beta}\}, & \text{if } q \le q_0; \\ J, & \text{else.} \end{cases} \tag{2}$$

where q is a random variable distributing uniformly in the interval [0,1], q_0 （$0 \le q_0 \le 1$） is a parameter, J is a random variable generated by probability distribution, and N_i^k represents the set of adjacent nodes which ant i can reach directly.

2) Local Search Strategy

Local search is a commonly used method for the solution of combinational optimization problems. It can find a high quality solution in a reasonable time through searching the neighborhood of the current solution. Pheromone is updated according to the optimized solution, and while construct the next path, the ant can find a better solution guided by the pheromone. After path construction, 2-opt [9] is used to optimize the iteration optimal solution, and fitness of the new solution will be calculated again. If the value of new fitness is larger than that before the local search strategy was carried out, then the new solution will replace the original solution, otherwise the original solution remains unchanged.

3) Mutation Strategy

Although local search strategy can speed up the convergence rate, it will lead to algorithm stagnation, that is to say, the probability of local optimum will increase. In order to get faster convergence speed, increase the diversity of the population, and expand the search range, IMMAS adopt mutation with a certain probability to jump out local optimum effectively. For each node, the mutation happens when 0 changes to 1 or 1 to 0.

B. Algorithm Implementation

The specific steps of feature selection through MMAS are as follows:

Step 1: Generate ants and build paths by pseudorandom rule and local pheromone update rule.

Step 2: Evaluate the solution through the fitness function. The fitness function is defined as:

$$F(k) = \frac{R(k)}{1 + \lambda \cdot n(k)}. \tag{3}$$

$F(k)$ is the fitness value of solution *k*, $R(k)$ is the correct classification rate of solution k, n is the feature number of k, and λ is the weight parameter of *n(k)*.

Step 3: Search a better solution in the neighborhood of iterative optimal solution according to local search and mutation strategy.

Step 4: Pheromone of the best-so-far solution is updated.

Step 5: Determine whether the maximal iteration number is reached. If reached, algorithm ends; otherwise, go to step 1.

V. EXPETIMENTAL RESULTS AND ANALYSIS

Our research chose 242 groups of effective signals, each of which contains the data of calm, happiness, surprise, disgust, grief, anger, fear. The features extracted from calm state were used for feature matrix normalization. Then IMMAS combined with Fisher was used for feature selection and classification. The ant number in IMMAS is 104, which equals to the feature number. The program runs for 50 times, and the result of recognizing six emotions respectively are shown in Table I.

TABLE I. RECOGNITION OF SINGLE EMOTION

Emotion	Dimension of Original Features	Dimension of Optimal Feature Subset	Best Recognition Rate	Average Recognition Rate
Happiness	104	15	75.36%	70.78%
Surprise	104	9	81.48%	76.39%
Disgust	104	12	74.67%	69.71%
Grief	104	50	87.88%	83.39%
Anger	104	7	75.89%	65.95%
Fear	104	20	81.43%	78.43%

TABLE II. RECOGNITION OF SINGLE EMOTION (LIMMITE THE DIMENSION OF THE OPTIMAL FEATURE SUBSET)

Emotion	Dimension of Original Features	Dimension of Optimal Feature Subset	Best Recognition Rate	Average Recognition Rate
Happiness	104	3	73.91%	63.62%
Surprise	104	5	79.63%	77.41%
Disgust	104	4	68.00%	67.79%
Grief	104	5	81.82%	75.49%
Anger	104	6	76.79%	69.61%
Fear	104	5	78.57%	74.83%

The experimental results show that it is feasible to recognize emotions using pulse signals.

From Table I we can see that while recognizing the six emotions respectively, surprise, disgust, and fear can reach good recognition effect. However, the high recognition rate of disgust is based on high dimension of feature subset.

If we limit the dimension of feature subset while selecting feature, as Table II shows, we can still obtain good recognition effects by optimal feature subsets with lower dimensions.

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