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Design and Implementation of Mobile Personal Emotion Monitoring System

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Abstract

It is suggested that emotion plays a significant role in rational and intelligent behaviors. People behave emotions in different ways, and may not be noticeable through outside appearances. However, physiological information may reveal the clue for emotions.

We proposed a mobile personal emotion monitoring system design, and proposed an adaptive algorithm that can help recognize user's emotion state by using physiological sensors. We applied the dimensional analysis approach and adopted IAPS (International Affective Picture System) to manipulate psychological experiments. We also proposed an emotion recognition learning algorithm. It would extract each pattern of emotions from cross validation training and can further learn adaptively by feeding personalized testing data. We measured the learning rate of each subject which reveals incremental enhancement. Furthermore, we adopted a dimensional to discrete emotion transforming concept for validating the subjective rating. Compared to the experiment results of related works, our system outperforms both in dimensional and discrete analyses.

Most importantly, the system is implemented based on wireless physiological sensors for mobile usage. This system can reflect the image of emotion states in order to provide on-line smart services.

1、Introduction

Emotion plays an important role in our life including rational thinking, making decision and so forth. We might know how to control it but we can not expect what the effect it will make. Emotion could be ignored when you do not pay attention but if it comes beyond you, you will be out of control. In recent years, due to the rapid advancement of hardware and signal processing techniques, we can measure the physiological signals by the physiological sensors. By further exploring the relation between physiological data and emotions, we will be able to design and implement a mobile personal emotion monitoring system. This system is designed to be mobile, by collecting personal physiological information through wireless sensor networks to determine the emotion status, and possibly give a warning for unhealthy emotions if needed.

Psychology and psychophysics have found some common features on a lot of traditional experiments. In fact people express personal emotions would be different because of environment, culture, education and so on. However, people do not behave in different ways in physiological signals. In general once a person has received an external stimulation like fear, physiological information should show the same way. For example, if we feel afraid, the heart rate will increase. The system we proposed can on-line recognize human emotions, it can help our living environment more smart or more health care. More specifically, it can provide considerate services. E.g. when the member of the room appears to be in the negative emotion, the system could detect the event and provide some service like playing music to ease the member's emotion.

Physically, human reflection or expression gives us some information and we learn how to recognize a person emotion by experiences, education and culture. We could teach the computer how to recognize human emotion by the information that physiological data provide. Machine learning brings us a good way to teach the computer. By training and extracting the features and attributes, the system will build the rule for recognizing each class of emotions. However, emotion is a quite complicated structure, and is different among people for acting an emotion state. We design the system using feedbacks to adapt the temporal or personal changes to enhance the correctness. Our system works with wireless physiological sensors on subjects. The system can distinguish what emotion state the subject is after a few training phases.

For the rest of the paper is organized as follows. Section 2 introduces the background knowledge about emotion models and some physiological sensors that psychologists often use. Section 3 will summarize the related work that describes how such an experiment is performed and the emotion classification method. Our detailed system implementation and algorithm will be explained in section 4. Experimental results are presented in section 5. And finally, section 6 concludes this paper.

2、Background

Figure 1 is the emotion model where two dimensional system in which emotional cues (e.g., facial expressions) are identified by registering their values on two orthogonal dimensions coding degree of pleasure and degree of arousal. This model can provide a mapping between predefined labels and the level of arousal and valence [1]. Here we defined 'pleasant' as 'positive', 'unpleasant' as 'negative', 'not aroused' as 'low arousal' and 'aroused' as 'high arousal' for the following paper.

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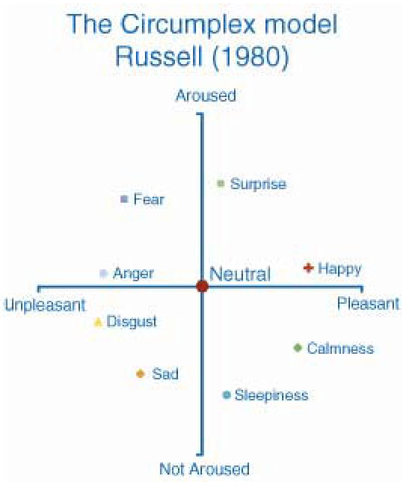

Figure 1: Russells' (1980) Circumplex model of emotion.

2.1、Emotion Model

Every day in our life, we are working under different emotion states. Some well-known emotion states in life are distress, terror, relax, joy and etc. These emotion states can be roughly defined on Figure 1. However it is hard to preciously indicate where a emotion should locate. Although there are many different opinions on how to label emotions, many researchers have the agreement of these few emotion states. We can refer this Figure 1 as the emotion model base.

2.2、Physiological Sensors

Physiological data is collecting from physiological sensors. There are some common signals [2] used as follows:

1. BVP (Blood volume pulse)
2. SC (Skin Conductivity)
3. RESP (Respiration rate)
4. EMG (Electromyography)

Subjects are wearing sensors that collect the movement of physiological index. Data will be calculated as a set of instance. Different emotions will come with different physiological data features. For example, terror emotion should show high SCL in user's skin, happy should show the movement in Zygomatic.

3、Related Work

In Section 3.1, we describe the related work of how to collect data from experiments. It elicits user to expose their emotion while using some sensors collecting physiological data. Section 3.2 will describe a particular participant of collecting data for a few months. It is focusing on a participant experiment and showing the result of recognition rate.

3.1. Experiment Design

An experiment environment should be designed to be able to elicit user different emotions that we can collect data for further training our system. It is suggested by psychologists that we can use the picture database assembled from the international affective picture system (IAPS) [3]. IAPS consists of 6000 pictures designed to induce emotions in people and each picture has been pre-rated for valence and arousal. The experiment is performed that the physiological data can be collected during testing participants' viewing a slideshow of images. In [4], 13 participants were viewing 21 images and rating each image valence and arousal. Then all the ratings were stored in a database to correlate how the participants felt when viewing the pictures with the original ratings from IAPS. This information was later used together with the IAPS ratings to train the emotion recognition system. Recognition rates for each affective state were performed for valence is 62%, and 67% for arousal.

3.2. Affective pattern classification of physiological data

This paper [5] develops a method for recognizing the emotion state of a person expressing one of eight emotions. An actress trained in guided imagery techniques, was asked to experience and intentionally express eight of emotion states using a computer controlled prompting system. Emotion states are no emotion, anger, hate, grief, love, romantic love, joy and reverence. EMG, SCL and Heart rate for the physiological data were collected and extracted with some features such as mean and variance. Fisher linear discriminant projection [6] were applied for pattern recognition analysis. The leave-one-out cross validation were adopted for recognition rate analysis. The Fisher projection is shown as follow:

$$S_W = \sum_{i=1}^{c} \sum_{x \in X_i}^{n} (x - m_i)(x - m_i)^t \quad \ldots\ldots(1)$$

$$S_B = \sum_{i=1}^{c} n_i (m_i - m)(m_i - m)^t \quad \ldots\ldots(2)$$

where m_i means sample mean for class i, m means total sample mean. x is a feature vector. W is the projection matrix whose columns, w_i correspond to the largest eigenvalues in (3)

$$S_W^{-1} S_B w_i = \lambda w_i \quad \ldots\ldots(3)$$

$$y = W^T x \quad \ldots\ldots(4)$$

y is the vector on projection space. Based on the analysis of projection space with the leave-one-out cross validation, recognition rate in the emotion set, anger and peaceful, are 90% and 98%, respectively. High and low arousals are 81% and 86%, separately. Positive and negative valences are 75% and 53%, respectively.

4、System Implementation and Recognition Algorithm

4.1、 System Implementation

We performed our experiments on a closed room. 24 images were played during the experiment to elicit participants' emotions. There are three classes of emotion, namely, positive, neutral and negative in valence and three classes of arousal which are low, medium and high. Each class has 8 pictures (objective). We collected the physiological data: SCL, RESP, BVP and EMG during viewing the images. Each picture took about ten seconds. The system implementation is shown as in Figure 2.

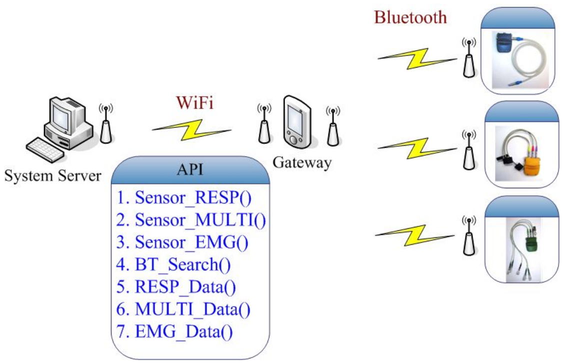

Figure 2: System Structure

Each participant was attached the wireless Bluetooth sensors. With the mobility concern and distinguishing among users, each participant also carried a PDA which can locally handle the data collection and first-aid monitoring. Because the distance between personal sensors and the gateway is very near, the power consumption will not be too severe. If the PDA detects something that is emergent, it can autonomously inform the server. Otherwise, it can accumulate the data up to a certain amount, then transfer to the server. Thus, the system will be very energy efficient. In the other way, we also design many API, such as sensor_RESP, sensor_MULTI, sensor_EMG, which can connect to the designated sensors. RESP_Data, MULTI_Data, and EMG_Data can collect the sensor's data. With these APIs, someone will be able to implement any monitoring algorithm on top of the system very flexibly. System server is in charge of more complex computations such as feature extracting and emotion recognizing. PDA is equipped with WiFi and Bluetooth device as a gateway to transfer data between sensors and the server. Using WiFi will make the communication distance between the PDA and the server longer. The system server can issue requests such as physiological connect or disconnect to some participant's sensors through his/her PDA using the API commands we developed. With this platform implementation, now we are ready to perform some experiments for training and for real recognition testing.

4.2、Recognition Algorithm

We are using mean, standard-deviation, slope of data movement on physiological data to form the feature set. 20 participants were taking part in our experiment. Their ages are between 20 ~ 30. Our algorithm to analyze the physiological data is shown in Figure 3.

The left part of Figure 3 is called 'training phase' which selects features for each emotion state. The right part is called 'testing phase' which modifies each emotion patterns according to personalized data. I.e. the 20 participants' data were fed into the training phase with cross-validation to extract features. We use support vector machine (SVM) [7] for classification. In the testing phase, we feed back the on-line testing data to re-build our training model in order to obtain more personalized features. Here, we define a learning rate to evaluate the performance. We expect that after several times of adjustment, the system will perform more accurately and indeed adapt to the user. The learning rate (LR_k) is defined as followed:

$$LR_k = \frac{Accumulative\_correct + Future\_correct}{n} \quad (5)$$

k means the k-th test. Accumulative_correct is the number of the correct class recognition from the beginning up to the current test data. Future_correct is the number of the correct class recognition using the modified features up to the k-th feedback personalized data. n is the total number of testing data. Therefore, as k increases, we can see the correct for the rate by the values of LR_k. It will interprete the effect on the future incoming testing data if we do add a new instance to the training model instances and rebuild training model.

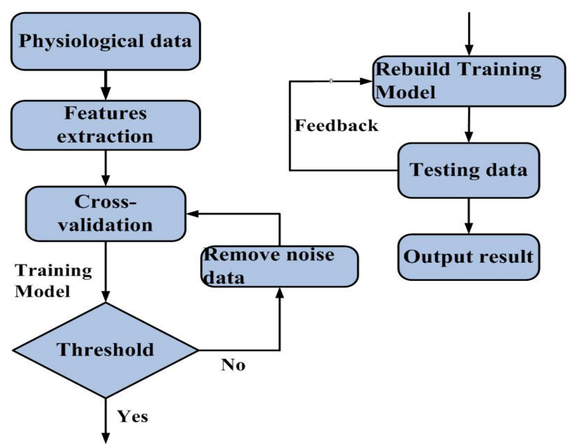

Figure 3: Recognition algorithm

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As for subjective versus objective emotion comparisons, participants were also asked to rate their emotions by the Figure 4 & 5 which are based on Self-Assessment Manikin (SAM) affective rating system devised by [3].

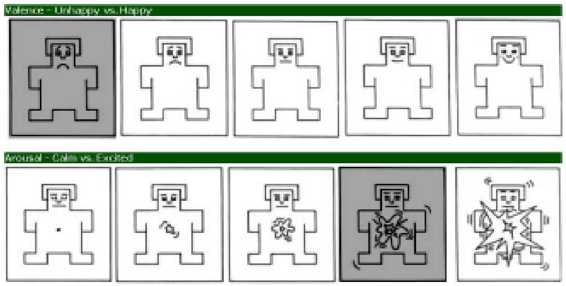

Figure 4: Valence and arousal rating item.

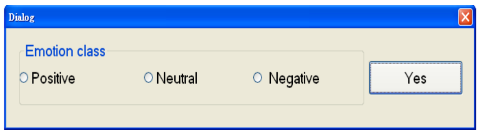

Figure 5: Emotional class rating selection

These rating selection from participants were taking into our recognition system as information. And then we use them to modify the recognition model to adapt user's pattern.

4.2、Dimensional to Discrete Emotion

So far we would treat the result of above emotion as dimensional emotion analysis. Here we will try to map the dimensional emotion to discrete emotion status. We will utilize the method proposed in [8]. We take the result of subjective rating of arousal and valence as an input for the Gaussian probability density function. We assume each discrete emotion state as a Gaussian distribution. Discrete emotion such as happy, sad or anger is considered to analyze. Once we have the mean and standard deviation, we can figure out the Gaussian distribution of the discrete emotion state. Figure 6 is an example of distribution of discrete emotion-surprise. Thus, in this method, if we can decide the valence and arousal from the system we address in the previous section, we can get the probability of surprise emotion. Therefore, we can distinguish from different discrete emotion states with its probability.

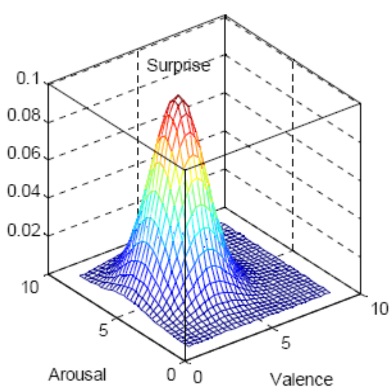

Figure 6: Probability distribution of surprise.

5. Experimental Analysis

5.1、 Experiment Design

Finally, we perform a real experiment to analyze the system we developed. We carefully choose 24 pictures from IAPS. Again, there are three classes which are positive, neutral and negative in valence. And another three classes is high, medium and low in arousal. Each picture is played on the screen of Notebook about ten seconds. We collect the physiological data from 20 participants during viewing pictures. The feature was calculated on the server. Then we test individual data to analyze the learning rate LR_k by introducing each one of the 20 participants' data to evaluate the robustness of our algorithm.

5.2、 Experimental Results

Two different modes are analyzed in this experiment. One is "objective" mode which means that the picture class for both valence and arousal is rated by the original IAPS. The other is "subjective" mode which means that the picture class is rated by participants.

Figure 7 shows the subjective learning rate for the valence recognition. The X-axis represents time moving of k-th test data. The Y-axis represents learning rate movement. As we feedback more test data, i.e. time (k) increases in the Figure 7, we calculate the learning rate by (5). It is obviously that we can find the learning rate of subjective mode is gradually increasing. It means that our algorithm have become "smarter" and personalized adaptive. We can see the same result in the objective mode shown in Figure 9.

For the arousal recognition, Figure 8 shows that the learning rate of the subjective mode is going up just in the beginning, and remains constant lately. However, in the objective mode, the learning rate is increasing as in Figure 10.

Table 1 shows the comparisons of the recognition rate for two modes in individual valence ratings. Obviously, the recognition rate of the subjective mode is higher than that of the objective mode. The reason is wide variations in individual response patterns due to gender, personality type and ethnic background. And also it implicates that the subjective rating is more reliable in comparisons with the objective rating.

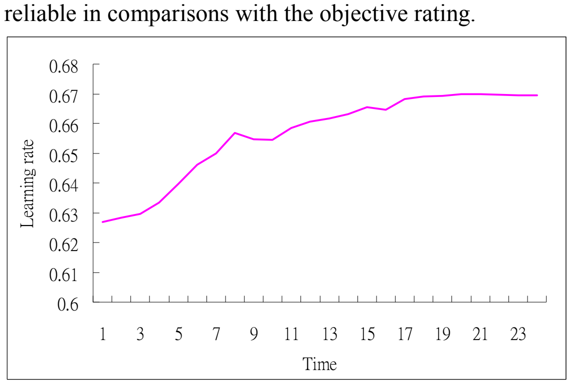

Figure 7: Learning rate of subjective in valence.

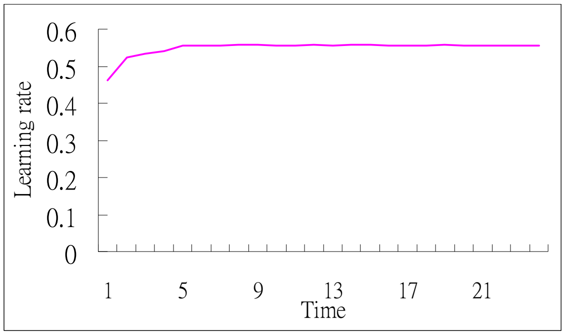

Figure 8: Learning rate of subjective in arousal

Table 2 shows the comparisons of the recognition rate for two modes in individual arousal ratings. We can see the similar result except the rating of the subjective medium which is 23.37%. It is because subjective rating on medium does not have enough instances in comparisons with low and high instances. Under this situation, the medium case will have less chance of recognizing correctly.

Table 1: Comparison of objective and subjective recognition rate in valence

	Positive	Neutral	Negative
Objective	46.55%	38.02%	40.52%
Subjective	68.67%	59.48%	54.45%

Table 2: Comparison of objective mode and subjective recognition rate in arousal

	Low	Medium	High
Objective	42.64%	53.26%	38.88%
Subjective	56.60%	23.37%	49.51%

Table 2 is focusing on arousal and we found the recognition rate of subjective medium seems to be lower than others.

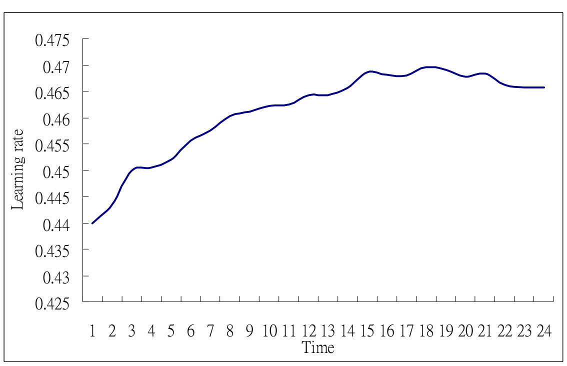

Figure 9: Learning rate of objective in valence.

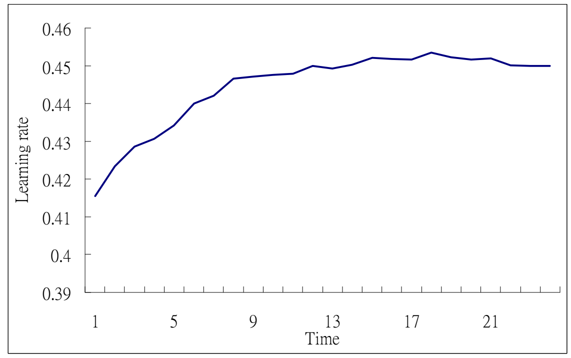

Figure 10: Learning rate of objective in arousal.

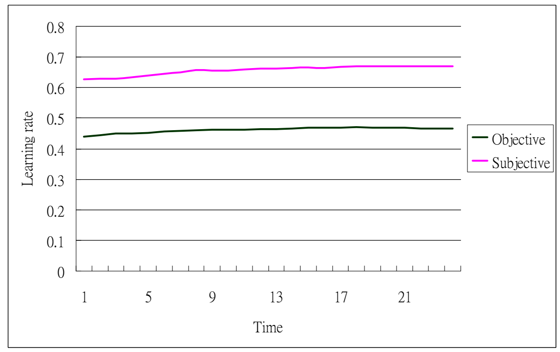

Figure 11: Comparison in valence.

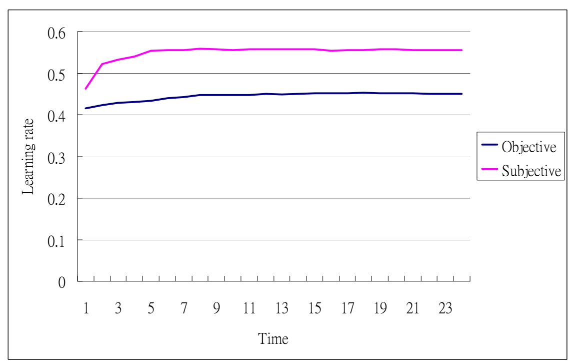

Figure 12: Comparison in arousal

Figure 11 and 12 show the results together with subjective and objective modes for valence and arousal, respectively. Obviously, we can observe from the figures that the more instances added into the system, the higher accurate recognition rate. From the limit of instances that we can perform the experiments, we still can find the result showing an increasing trend. For adapting in the personalized usage, we believe that this system will perform stable recognition ability if we add enough instances for each class.

5.2、 Dimensional to Discrete Emotion Results

Finally, we try to map our dimensional recognition result to discrete emotion states to see if we get the same good performance. For simplicity, we take only two extreme emotion states, namely, disgust and happy. Figure 13 is the steps of our analysis of dimensional to discrete emotion.

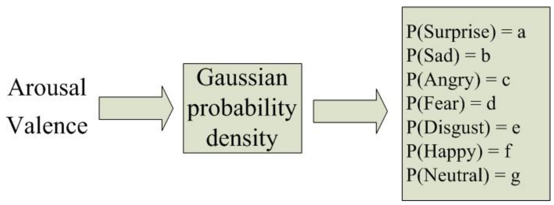

Figure 13: Probability of discrete emotion states

Here we checked the probabilities *e* and *f*. For the disgust case, if the probability difference between *e* and *f* is more than 80% and *e* is more than *f*, the result is marked as 'absolute accurate'. If the probability difference between *e* and *f* is more than 50%, less than 79% and *e* is more than *f*, the result is marked as 'probably accurate'. Otherwise the result is marked as 'does not match'. It is also the same as in the happy case. We verified the result for difference probability of disgust and happy. 92.5% is reached in our experimental result for 'absolute accurate', 5% is for 'probably accurate' and 2.5% is for 'does not match'. So the results of the two extreme discrete emotion states are well distinguished according to the subjective valence and arousal ratings.

6. CONCLUSIONS

In this paper, we implemented a monitoring system for recognition of emotion states. Our design and implementation is quite suitable for mobile and personal emotion state recognition. We verified the emotion recognizing rate for different cases on valence and arousal. Learning rate has gradually growing in either case. This means that our algorithm can perform well if we have enough data to make the recognition system more intelligent. Finally we also verified the dimensional to discrete emotion result. We found out the results of the two extreme emotion states are well distinguished.

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