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Emotion and Cognitive Reappraisal Based on GSR Wearable Sensor

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Abstract

Various wearable equipment enables us to measure people behavior by physiological signals. In our research, we present one galvanic skin reaction (GSR) wearable sensor which can analyze human emotions based on cognition reappraisal. First, We research the factors of emotional state transition in Arousal-Valence-Stance(AVS) emotional space. Second, the influence of the cognition on emotional state transition is considered, and the reappraisal factor based on Gross regulation theory is established to correct the effectiveness from cognitive reappraisal ability to emotional state transition. Third, based on the previous work, we establish a GSR emotion sensing system for predicting emotional state transition and considering the correlation between GSR signals and emotions. Finally, an overall wearable sensor layout is built. In the experiment part, we invited 30 college students to wear our GSR sensors and watch 14 kinds of affective videos. We recorded their GSR signals while asking them to record their emotional states synchronously. The experiment results show different reappraisal factors can predict subjects' emotional state transition well and indirectly confirm the feasibility of the Gross regulation theory.

Keywords

wearable equipment; emotional state transition; AVS emotional space; Gross regulation theory; GSR emotion sensing system

1 Introduction

The state-of-the-art technology has made it possible to monitor various physiological signals for analyzing human behavior, cognitive science, social psychology, and group perception [1]–[3]. The collected data from a person donning a wearable sensor can be saved digitally for later research. Therefore, we can learn the effects of the external stimulus environment and our day-to-day actions, and establish some wearable sensors to make it convenience to monitor the human mental health for further treatment [4].

Galvanic skin reaction(GSR) is commonly used for measuring emotional activities. GSR reflects the sweat gland secretion reaction, which is different from the amount of sweating, changing by a subject's emotional arousal, finger temperature and finger activity. Changes in emotional arousal can cause significant skin electrical response, which has been widely agreed by researchers [5]. There are many studies of emotion recognition based on GSR signals. For example, the subject's emotion is induced by different videos while the GSR signal is being recorded and processed by Immune Particle Swarm Optimization algorithm for classification [6]. Besides, a multi-variant correlation method is proposed to detect the affective physiological changes in multi-subject GSR, the first derivative of GSR (FD_GSR) and heart rate(HR) [7].

The activation of emotion needs a series of external factors, and also needs internal cognitive factors which can be seen as the complex emotional state transition [8]. The emotional space based on dimension can descript human emotional state transition clearly with the diversity of human emotions. Emotional space with cognitive analysis can adjust some unexpected and unpredictable situation to help promote the natural and harmonious human-computer interaction experience. In the Gross emotional regulation theory, cognitive reappraisal strategy is based on individual cognitive ability to understand the event, change the emotional experience in order to rationalize expression [9].

In our research, we present one GSR based emotion sensing system to predict human emotional state and design the wearable sensor. The influence of the cognition on emotional state transition is considered and the cognitive reappraisal function

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with reappraisal factor is established. Section 2 describes the Arousal-Valence-Stance(AVS) emotional space with the factors of emotional state transition taken into consideration. Section 3 shows the establishment of the emotion cognitive reappraisal function. Section 4 presents the overall GSR based emotion sensing system. Section 5 describes the design of the wearable sensor. Section 6 then measures the experiment by inviting 30 subjects to watch emotional video, and the results and discussion are shown in Section 7. Section 8 is the conclusion and further plan.

2 AVS Emotional Space

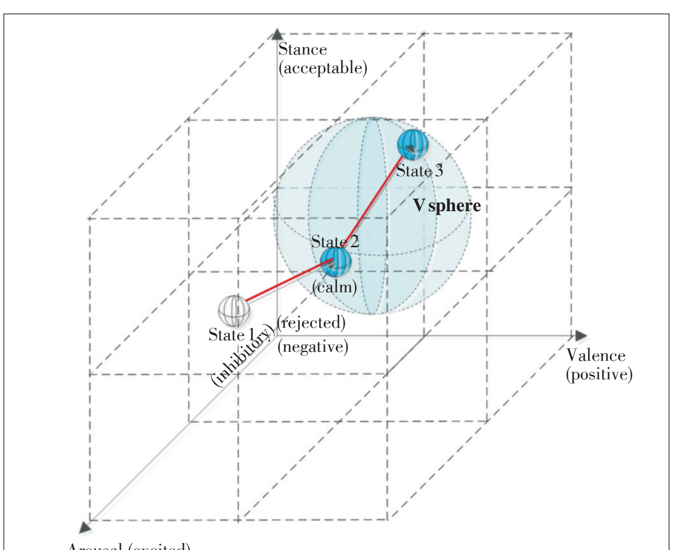
AVS Emotional Space [10] has three dimensions: valence, arousal, and stance. Valence represents the level of pleasure. Arousal represents the level of exciting and stance represents if people have control in this situation. We measure all the emotion activities in this three-dimension based space (**Fig. 1**).

In our hypothesis, the distance between two different emotional states in AVS can reflect the probability of their transition indirectly. Close distance of emotional states can be seen as the same kind of basic emotion, such as happy, sad, angry, surprised, fear, disgust and calm. S_i means one specific emotional state i, P_{ij} means the probability of transition from state i to state j. We define the coefficient λ which reflects the degree of transition difficulty :

$$\lambda = P_{ij} \cdot \beta, \tag{1}$$

$$P_{ij} = normalize \frac{\iiint \mathrm{d}v\mathrm{d}a\mathrm{d}s}{V_{sphere}(diameter = |s_i - s_j|)}, \tag{2}$$

where β means one constant, v=valence, a=arousal, and s=stance. The farther the distance, the harder the transition, and vice versa. Researchers have done a lot of studies about the process of emotional state transition only caused by emotional stimulus and have made a lot of useful results [11], [12]. Thereby in our research the emotional factors correct the effectiveness of emotional cognition reappraisal based on GSR signals.



▲**Figure 1. AVS emotional space.**

3 Emotional Cognitive Reappraisal

In the natural emotional interaction, the emotional change is affected by a series of external and internal factors. It is not only affected by external emotional stimulation and the current emotional state of the impact, but also by the individual's own emotional cognitive ability. Psychologist Gross pioneered the emotional regulation strategy. Gross' cognitive reappraisal strategy based on the individual's cognitive ability to understand the event change the emotional experience so as to rationalize this matter, which is the key to emotional regulation process [13]. Gross argues that the process of emotional regulation consists of five parts: situation selection, situation correction, attention distribution, cognitive reappraisal, and expression inhibition. Among them, the first two are based on the changes from the external environment, while the rest are for the individual's subjective will or behavior carried out. Cognitive reappraisal occurs before the emotional response, and the emotional state is reappraisal and adjusted; expression inhibition occurs after the emotional response behavior. The cognitive reappraisal strategy as a priority regulation strategy reduces the negative emotional experience better and emotional state tends to be alleviated. The hysteresis reappraisal factor is defined as $\alpha \in (-10,10)$, and we suppose the emotional suppression factor τ is:

$$\tau = \frac{2}{\pi} \arctan \alpha, \tau \in [0,1). \tag{3}$$

The subject's negative emotional state transition will be alleviated when this person has strong cognition ability. In order to follow this definition, we suppose the emotional state transition probability as follows:

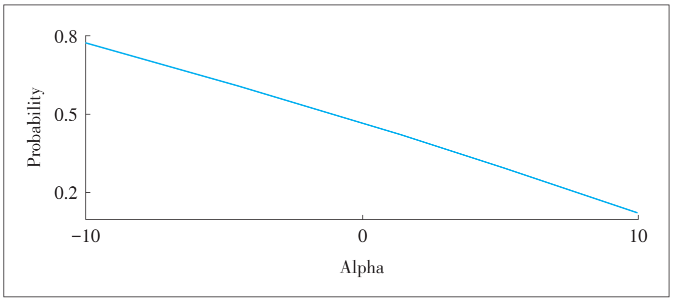
$$P_{statei \to statej} = normalize(1+\tau)P_{ij},$$
when state i is more negative than state j. (4)

$$P_{statei \to statej} = normalize(1-\tau)P_{ij},$$
when state i is more positive than state j. (5)

Fig. 2 shows the simulation result.

4 GSR Based Emotion Sensing System

General skin current movement has a certain resistance parameter, but in the external emotional stimulation, the skin conductive current increases, while the resistance decreases. Therefore, GSR is considered to be one of the objective indica-



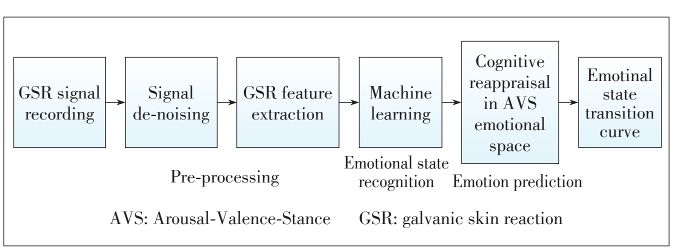
▲Figure 2. The probability of transition from the positive state to negative state.

tors of emotional determination. For example, when a person is frightened or anxious, the blood pulse tends to rise. Based on this, we present an emotional sensing system for emotion prediction by cognitive reappraisal.

As illustrated in **Fig. 3**, the process of emotion sensing system in GSR signal in this study has five main steps: 1) GSR signal recording; 2) GSR signal de-noising; 3) GSR signal feature extraction; 4) machine learning for current emotional state recognition; 5) cognitive reappraisal in AVS emotional space for emotional state transition prediction. The second step is referred to pre-processing, and in this paper we use the second-order Batter worth low-pass filter to reduce high frequency noise. For feature extraction, this paper measures GSR signal by Fast Fourier transform(FFT) and extracts 28 features in time domain and 6 features in frequency domain from 0.08 Hz to 0.2 Hz. After all the features are generated, they are provided to a machine learning model to differentiate the emotional state from the calm state of a subject. In particular, this paper employed a support vector machine (SVM) for this learning model and emotional recognition which is not described in detail here. A database for emotion analysis using physiological signals(DEAP) [14] is used for learning.

In order to describe the influence of external stimuli in the current state for emotion transition, the transition relationship between emotional states is analyzed, and hidden Markov model (HMM) is presented [15]. Expectation maximization (EM) algorithm is used to obtain the statistical state transition probability. Besides these, we combine the HMM model with cognitive reappraisal for regulation based on cognition.

Figs. 4, **5**, and **6** are the GSR signals from the experimental collection of a subject in calm, happy, sad emotional state respectively. From the figure we can see that in different emotional states, the skin levels of electrical differences are different, and the variation ranges are also different. Among them, the happy emotional state has strong fluctuation of GSR, and in this situation, since we activate the subject at first second, the appearance of a new stimulus may artificially shorten the half recovery time of the response to the previous stimulus.



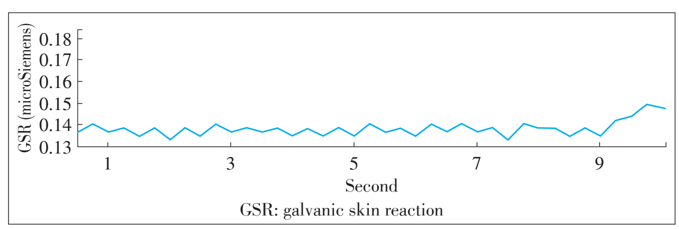
▲Figure 3. Emotion sensing system.

5 Wearable Sensor

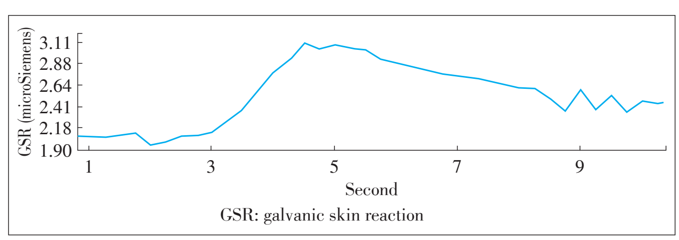
As shown in **Fig. 7**, the wearable sensor contains GSR electrodes, sensor circuit, multi-channel data acquisition system for other physiological signals recording, and Bluetooth 4.0 for data transmission. The electrodes are measured using medical silver chloride electrode. The silver electrode sheet whose area is 1 cm^2 is adhered to the sticker with a conductive paste. When the subject wears it, the electrode patch is attached to the wrist skin.

After wrapping two electrodes around the left wrist, we calculate the GSR value by using one resistance as seen in Fig. 7. The capacitor is used for low-pass filtering while the resistance is used for high frequency filtering. And single chip is used for calculating the D-value and conducting the sampling frequency. The GSR's useful signal frequency range is mainly concentrated below 0.2 Hz. According to the Nyquist sampling theorem, the sampling frequency in the sampling process is set to 20 Hz.

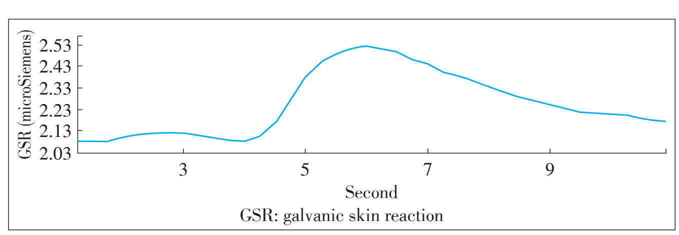
In our project, Bluetooth 4.0 is chosen for transmission



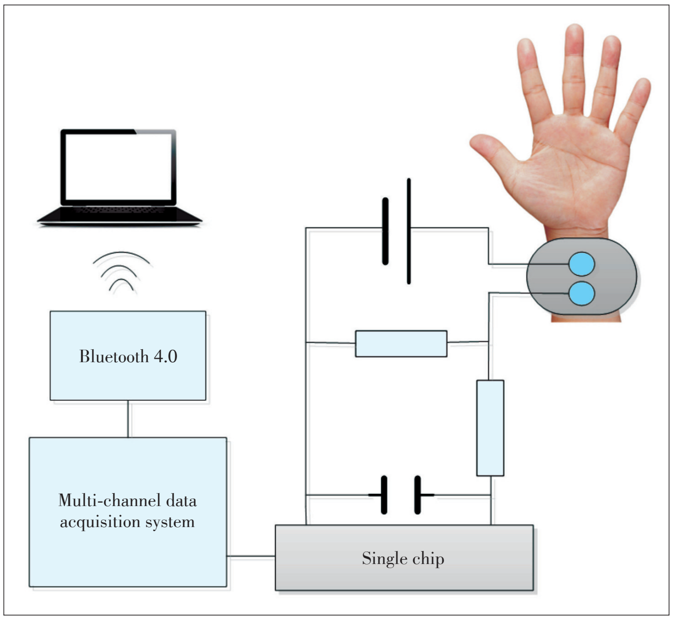
▲Figure 4. GSR signal curve under calm emotional state.



▲Figure 5. GSR signal curve under happy emotional state.



▲Figure 6. GSR signal curve under sad emotional state.



▲Figure 7. Wearable sensor.

which has advantages of low power consumption and stability.

6 Experiment

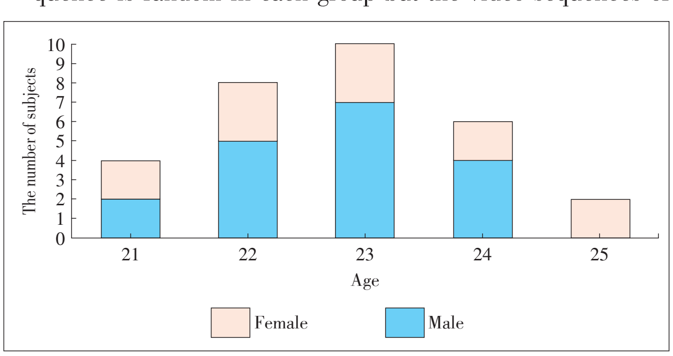
In our experiment, we invited 30 volunteers for testing the GSR based emotion sensing. The 30 subjects' age distribution is from 21 to 25 years old (**Fig. 8**), and all of the subjects are in healthy mental condition.

Before the experiment, the subjects learned how to record their valence, arousal, stance by self-assessment [16]. **Fig. 9** shows the self-assessment manikins. The valence, arousal, stance is ranged from 1 to 9.

The 14 emotional videos as the stimulus were chosen from Last.fm which had been proven effective [14]. Each video was1 minute. Every volunteer wrapped the wearable sensor around the left wrist, and 30 volunteers are divided into 3 groups.

The specific experiment steps are as follows:

1) Choose two groups, make sure these subjects keep calm at the first, and then let them watching 14 videos whose sequence is random in each group but the video sequences of two groups are the same
2) Self-assessment of their valence, arousal, stance
3) Record their GSR signal and measure them by emotion sensing system to obtain the emotion prediction
4) Compare the front 1 minute emotion state with current self-assessment
5) Let each subject of the rest group watch the same kind of videos 5 times, with the kinds of video for everyone being different
6) Repeat Steps 2–5.



▲Figure 8. The age distribution of subjects.

7 Results

Table 1 shows the R-square value and covariance of the transition curves described by emotion prediction and subjects' self-assessment. It can be found that the arousal's correlation coefficient is bigger than valence's, which indicates GSR has a higher correlation with the arousal [5]. When individual difference is taken into account, every subject has a different reappraisal factor α which is observed by the emotional state transition curve of self-assessment (**Fig. 10**). Then, we obtain the factors fitting this curve most. The result shows that different reappraisal factors can predict subjects' emotional state transition well.

In the rest group test, **Fig. 11** shows one typical subject's

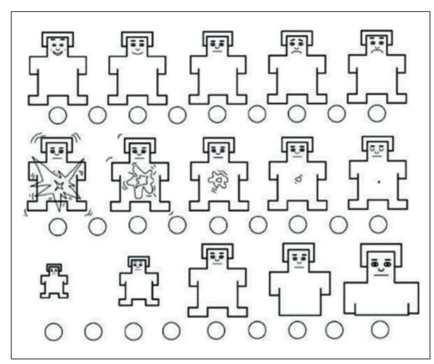
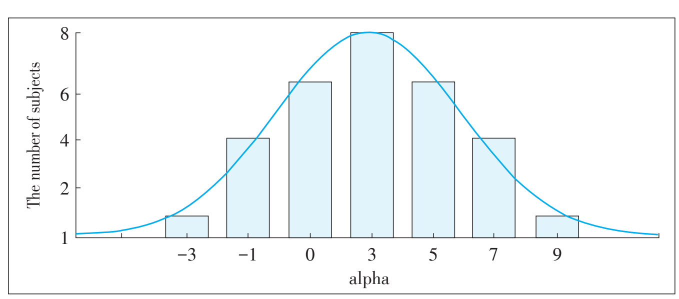


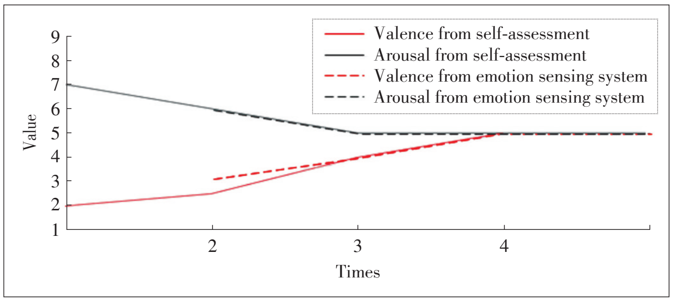
Figure 9.▶
Self-assessment manikins.

▼Table 1. The correlation between the prediction and self-assessment

Valence		Arousal	
R-square	Cov	R-square	Cov
0.325	0.667	0.628	0.9673



▲Figure 10. The distribution of subjects with different reappraisal factors.



▲**Figure 11. The transition curve from self-assessment and emotion sensing system.**

emotional state transition curve of self-assessment and the curve from emotion sensing system under sad stimulus. The result confirms Gross cognitive reappraisal strategy that the negative emotional experience is reduced better and emotional state tends to be alleviated by considering the cognitive effect.

8 Conclusions

This paper focuses on the cognitive effect on emotional state transition based on GSR wearable sensor. In the result, we find different reappraisal factors can predict subjects' emotional state transition well and indirectly confirms the feasibility of the Gross regulation theory. In the future, we will focus on the deep learning algorithm to optimize the result of emotion recognition. The continuous emotion detection will also be considered.

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