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An Entropy Measure of Emotional Arousal via Skin Conductance Response

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Abstract

Whether different affective states have specific physiological activation patterns still does not have an exact interpretation and clear validation. Skin Conductance Response (SCR) is under strict control of the autonomic nervous system, providing an efficient way to measure the emotional reactions. Since the emotional SCR signals are always short and noisy, it is of great value to study the methods suitable for short-term SCR analysis. According to the characteristic of SCR signal, we proposed a symbolic method and the symbolic information entropy, further, applied the method to analyse emotional SCR signals. Experiment results show that the symbolic information entropy of SCR is in accordance with the arousal level of emotions, and SCR is more sensitive to the variations of emotional arousal rather than to valence. Symbolic information entropy is less influenced by noise and non-stationary, providing an effective method in analyzing SCR signals or other complex physiological signals.

Keywords: Skin Conductance Response; Affective Computing; Symbolization; Information Entropy

1 Introduction

Researches on emotion have shown that autonomic responses vary according to reports of affective valence (i.e. pleasant or unpleasant) and arousal (i.e. calming or stimulating), which are two motivational determinants of emotions [1]. Skin Conductance Response (SCR) provides readily accessible autonomic indices, since SCR is under strict control of the sympathetic branch of the nervous system. SCR reflects the change in skin conductance caused by rapid fluctuations in eccrine sweat gland activity, which is the result of the liberation of acetylcholine by the sympathetic nervous system [2]. Many researchers have demonstrated [3-5] a tight relationship between emotional reactions and SCR. When an emotion-inducing events occurs, sympathetic nerve activity will rise to dominance, which is reflected in the increase of sweat gland secretion. By calming down the emotion, sympathetic tension decreased, and parasympathetic activity increased, thereby the sweat gland secretion decreased. This regulation process is very complex and differs in different affective states. Moreover, other factors, cognition activities, for instance, also have noticeable functions to

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SCR. Although we know that emotional events may raise the physiological arousal and organ's activation, however, whether different affective states have specific physiological activation patterns still does not have an exact interpretation and clear validation. In this study, we wanted to observe whether different emotions could induce specific SCR patterns, both on valence and arousal states.

Since SCR is nonlinear and non-stationary, more intensive analysis should be done to get a better understanding of the underlying dynamic condition. In addition to conventional linear methods, many nonlinear dynamical methods and complexity measures have been used in analyzing the SCR. These studies are helpful in revealing the potential law and physical nature of the emotional and cognitive activities. Common methods include Lyapunov exponent, correlation dimension, multi-fractal spectrum, and entropy measures as well [6-9]. Entropy first appeared in macroscopic thermodynamics, and Boltzmann makes entropy has a microscopic meaning of the molecular level. Although Shannon entropy was proposed for information theory, it has a general meaning. In a broader sense, Boltzmann entropy in thermodynamics is a special case of Shannon information entropy. Entropy is no longer confined to the thermodynamic and molecular thermal motion, but the nature of uncertain events. Information entropy and its variants are widely used to describe the irregularity of various signals [10-13]. Among them, approximate entropy (ApEn) and sample entropy (SampEn) are most commonly used in measuring the complexity of biological data [14, 15]. ApEn measures the "likelihood that runs of patterns that are close remain close on next incremental comparisons", and has been suggested to measure the complexity of short data sets [16, 17]. Richman and Moorman [15] discussed some shortcomings of ApEn, and they pointed out that ApEn includes a bias towards regularity inherently, as it will count a self-match of vectors. SampEn was recommended as an algorithm to counteract the shortcomings of ApEn [15]. Increase in SampEn is often associated in increases in complexity. However, Luiz et al. [18] showed the strong limitation of SampEn as a complexity metric. They found that a shuffled version of the Heart Rate Variability (HRV) series is often assigned with higher values of SampEn than the original HRV series, quite the opposite expected from a complexity measurement, for the SampEn values of HRV series of healthy subjects are often lower than that of the atrial fibrillation ones. In addition, Yentes et al. [14] demonstrated that both ApEn and SampEn are extremely sensitive to parameter choices, especially for very short data sets, $N \leq 200$. In stead of analyzing the complexity of original time series, symbolic information entropy measures the complexity of symbol sequence of SCR signals. Symbolization is an important means of dynamical system analysis. Its significance lies in coarse-graining off part of the details, while retaining the interesting part [19]. Guzzetti et al. [20] transformed HRV series into a symbol sequence of six symbols and found that the rates of occurrence of the patterns of three successive symbols are useful in describing the short-time fluctuations. Appropriate coarse graining helps to obtain more rigorous conclusions. The greatest advantage of symbolization is less sensitivity to the noise, and the key part of the application is how to differentiate right symbol area to properly coarse grain the signal.

The emotional SCR signals are always short and noisy, so in order to observe the SCR patterns induced by different emotional events, we proposed a dynamic symbolic method of time series and the symbolic information entropy, which are applicable in the short-term SCR analysis. Firstly used four symbols to portray the SCR fluctuations, further used symbolic information entropy to indicate the complexity of SCR symbolic sequences. The study found that emotional events induce skin conductance responses varying according to arousal, but not to valance. Thus, SCR measurement may offer a way to perceive the intensity of personal emotional feelings, but it is hard to know whether the emotion is positive or negative by SCR alone.

2 The Symbolization of SCR

SCR is recorded by measuring the changes in skin conductance at the surface caused by sweat secretion. Since sweat is a weak electrolyte and good conductor, the filling of sweat ducts results in many low-resistance parallel pathways, thereby increasing the conductance of an applied current [21]. SCR is usually measured at the palmar sites of the hands or the feet where the density of sweat glands is the highest (>2000/cm^2). The activities of eccrine sweat glands are solely determined by the sympathetic axis of the ANS, and therefore, SCR provides a sensitive and convenient measure for assessing alterations in sympathetic branch of the ANS. A stimulus (e.g., a startle event) often triggers a rapid rise and biphasic decay in skin conductance (Fig. 1). We proposed a dynamic symbolic method of time series which reflects the rising speed and intensity of the response waveform. The SCR symbolic sequence contains four symbols, and the symbolic method is defined as follows.

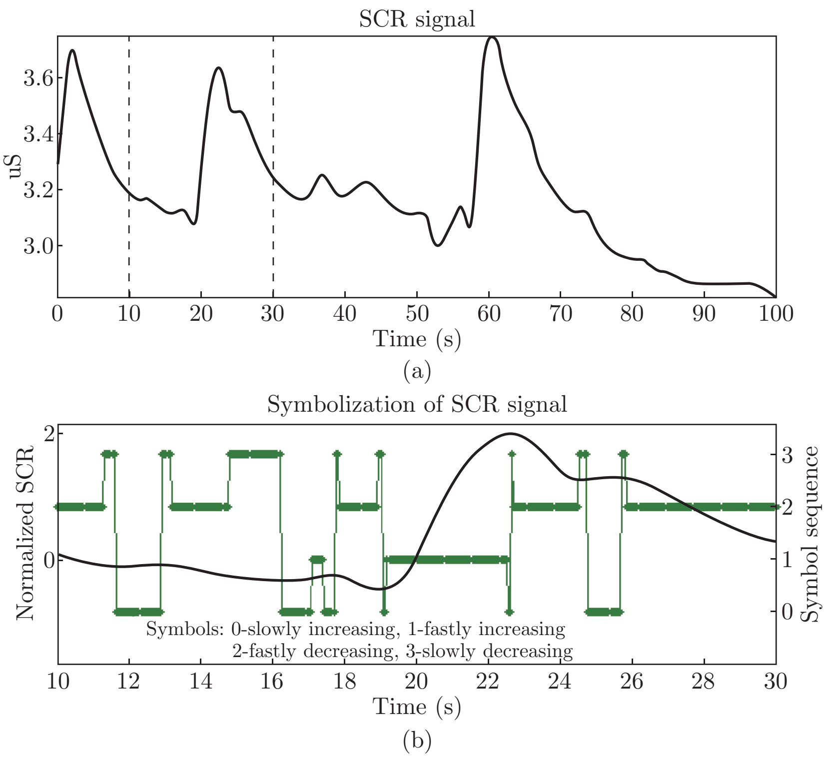

Fig. 1: The Symbolization of SCR. The Symbolization of the SCR fragment between the two dotted lines in (a) is shown in (b). The slowly increasing parts of the signal are encoded as 0, the fast increasing parts of the signal is encoded as 1, the fast decreasing part of the signal is encoded as 2, and the slowly decreasing parts of the signal are encoded as 3

First, normalize the SCR signal $X = \{x_i : 1 \le i \le N\}$ to mean 0 and variance 1:

$$\tilde{X}_n = \frac{X_n - \mu_X}{\sigma_X}, \quad n = 1, 2, \cdots, N, \tag{1}$$

where μ_X and σ_X are the mean and variance of X.

Then the symbolic sequence of SCR signal $S = \{s_i : 1 \le i \le N-1\}$ is defined as:

$$s_i = \begin{cases} 3, & x_{i+1} < x_i,\ x_i - x_{i+1} < k \\ 2, & x_{i+1} < x_i,\ x_i - x_{i+1} \ge k \\ 1, & x_{i+1} \ge x_i,\ x_{i+1} - x_i \ge k \\ 0, & x_{i+1} \ge x_i,\ x_{i+1} - x_i < k \end{cases}, \quad 1 \le i \le N-1, k > 0, \tag{2}$$

Symbol 0 denotes slow increase of the SCR signal, for the value of x_{i+1} is larger than x_i while the increase is lower than k. Similarly, symbol 1 denotes fast increasing, symbol 2 denotes fast decreasing and symbol 3 denotes slowly decreasing SCR waveform. k is a threshold which is used to differentiate the fast or slow change. When $k \to 0$ or $k \to \infty$, the symbolic sequence contains (0, 3) or (1, 2) merely, and is simplified into a two symbol sequence. In practice, we can use the standard deviation of the first-order difference of the SCR signal as k. Symbols here just represent the states, and their values do not make any sense.

A typical symbolic process is shown in Fig. 1. Fig. 1 (a) shows a SCR signal, and Fig. 1 (b) shows the normalized SCR fragment between 10 and 30 seconds and the symbol sequences of the fragment. First the SCR signal was normalized according to Eq. (1), and then the symbol sequence was calculated by Eq. (2). The parameter k is determined by the standard deviation of the first-order difference of normalized SCR signal and for the SCR signal in Fig. 1 (a) $k = 0.0038$. From Fig. 1 we can see that, the waveform of SCR is coarse grained, and only the information of fluctuating trends is retained.

3 Symbolic Information Entropy

Entropy is a non-negative quantitative description of the complexity of nonlinear time sequence. For random variable X with finite values, $P\{X = x_i\} = p(x_i)$, $i = 1, 2, \cdots, n$, $p(x_i) \ge 0$, $\sum_{i=1}^{n} p(x_i) = 1$, the information entropy is:

$$H(X) = H(p(x_1), p(x_2), \cdots, p(x_n)) = -\sum_{i=1}^{n} p(x_i) \log p(x_i), \tag{3}$$

where $p(x_i)$ is the probability of events x_i, n is the total number of events (state) that may occur. Obviously, for a deterministic variable X, $H(X) = 0$, and for random variable X, $H(X) > 0$. $H(X)$ increases with the increasing number of states n.

To find out the correlation between emotional stimuli and event-related SCR, first construct the m-dimensional vectors of SCR symbolic sequence by sliding window method:

$$X(n) = (x(n), x(n+1), \cdots, x(n+m-1)), \quad n = 1, 2, \cdots, N-m+1. \tag{4}$$

With window width m, vectors have $M = 4^m$ available modes. For example, there are 16 modes when $m = 2$, and the modes are: 00, 01, 02, 03, 10, 11, 12, 13, 20, 21, 22, 23, 30, 31, 32, 33. Among them, 01 denotes a change mode from slowly increasing to fast increasing in the waveform. The probability of each mode was calculated as follows:

$$p_i = \frac{n_i}{N-m+1}, \quad i = 1, 2, \cdots, M, \tag{5}$$

where n_i is the count number of mode i. Then the symbolic information entropy can be defined as:

$$SIE(m) = -\sum_{i=1}^{M} p_i * P_i, \quad P_i = \begin{cases} \log_2(p_i) & p_i > 0 \\ 0 & p_i = 0 \end{cases}. \tag{6}$$

Symbolic information entropy represents the average irregularity of each mode's occurrence. For example, for an ever slowly increasing line, its symbol sequence has only one mode 00 when $m = 2$, then the probability of mode 00 is 1, and the probabilities of other 15 modes are zero. The $SIE(2)$ of this slowly increasing line reaches the minimum entropy,

$$SIE(2)_{line} = -\left[1 * \log_2(1) + \sum_{2}^{16} 0\right] = 0,$$

that means the fluctuation pattern of the signal is rather simple, just the repetition of one mode. For the white noise, since the points are totally random, the probability of each mode in the symbol sequence is equal, $p_i = 1/16$, then the $SIE(2)$ of the white noise reaches the maximum entropy,

$$SIE(2)_{whitenoise} = -\sum_{1}^{16}\left[\frac{1}{16} * \log_2\left(\frac{1}{16}\right)\right] = 4.$$

The higer SIE represents higher irregularity of the fluctuation pattern of the signal.

4 Analysis on Skin Conductance Responses

The SCR data we used is taken from the MIT media lab affective computing group eight-emotion sentics database [22], the usage of the database for research purposes is permitted and the database is available from their website (affect.media.mit.edu). The database consists of measurements of four physiological signals and eight affective states. The four physiological signals are: blood volume pulse, electromyogram, respiration and skin conductance. We only use skin conductance here. The eight states are: (N)o emotion, (A)nger, (H)ate, (G)rief, (P)latonic love, romantic (L)ove, (J)oy, and (R)everence. Picard and Healey [22] used this database and achieved 81 percent recognition accuracy on eight classes of emotions, including neutral.

The physiological signals were recorded from one subject, a healthy graduate student with two years acting experience plus training in visualization. The data acquisition lasted for 30 days, and each day's session lasted for around 25 minutes. The subject sat in her quiet workspace early each day, at roughly the same time of day, and tried to experience eight affective states with the aid of a computer controlled prompting system and a set of personally-significant imagery she developed to help elicit the affective state. The order of expression of the eight states: no emotion, anger, hate, grief, platonic love, romantic love, joy and reverence. The database contains 20 day's data only as there are failures on certain days. Table 1 shows the subject's report on the images that she used to induce each emotion, the degree to which she found each experience arousing and the degree to which she felt the emotion was positive or negative.

From Table 1 we know the feelings of each emotion and the arousal and valence of each emotion. Valence and arousal are the two most common dimensions in classifications of emotions. In general, positive valence is associated with success, choice involving gains and negative valence

Table 1: The Subject's descriptions of imagery and emotional character used for each of the eight emotions [22]

Emotion	Imagery	Description	Arousal	Valence
(N)o emotion	blank paper, typewriter	boredom, vacancy	low	neut.
(A)nger	people who arouse rage	desire to fight	very high	very neg.
(H)ate	injustice, cruelty	passive anger	low	neg.
(G)rief	deformed child, loss of mother	loss, sadness	high	neg.
(P)latonic love	family, summer	happiness, peace	low	pos.
Romantic (L)ove	romantic encounters	excitement, lust	very high	pos.
(J)oy	The music "Ode to Joy"	uplifting happiness	med. High	pos.
(R)everence	Church, prayer	calm, peace	very low	neut.

is associated with failure, choice involving losses [23]. Low arousal is associated with low level of stimulation or motivation, actions requiring less efforts, while high arousal is associated with high level of stimulation or motivation, action involving more efforts [23]. We use symbolic information entropy to measure the irregularity of fluctuation patterns of SCR signal and try to find the relationship between symbolic information entropy with emotional valence and arousal.

SCR signals and other signals in the database were recorded by ProComp unit form Thought Technologies. The sample rate of SCR signal is 20 Hz. The skin conductance sensor measuring SCR signal from the middle of the three segments of the index and middle fingers on the palm-side of the left hand (with 11 mm Ag-AgCl electrodes and K-Y Jelly used for low-conductivity gel). The left hand was held still throughout data collection and the subject was seated and relatively motionless except for small pressure changes she applied with her right hand to the finger rest.

The database contains 20 day's data, and since there are eight affective states, there are 160 SCR signals in the data set. The length of each SCR signal is 100 seconds, 2000points. To calculate the symbolic information entropy of each signal, we should determine the threshold k used in the symbolization process, and the window width m of the symbolic information entropy.

The threshold k is determined by the average standard deviation of the first-order difference of the normalized SCR signals, $k = 0.0092$. If the difference of two consecutive points is larger than k, the change is regarded as fast, otherwise, slow.

Although larger m can reflect more complicated change modes of the signal, it needs longer data to gain accurate assessment of the probability of each mode. Brock et al. [24] discussed the relationship between m and data length N when they calculated BDS statistic. They carried out an investigation of time series with three sample sizes, $N = 100$, 500 and 1000, and suggested that m should be between 2 and 5. Kim et al. [25] illustrated the dependence of the statistic S which represents the correlation of the time series on m and N for the Lorenz system, they found that S fails to represent the true correlation when N decreases below 100, and within the range $2 \le m \le 5$, the quantity S represents the serial correlation for the wide range of values of N. Since the fluctuation patterns of SCR are not complicated, SCR changes slowly in most of the time and has a fast abrupt rising when stimulation occurs, 16 modes are enough to depict the fluctuation patterns of the signal. Therefore, we set $m = \log_4 16 = 2$.

For every normalized SCR signal $X = \{x_i : 1 \le i \le N\}$, the Symbolic information entropy $SIE(m)_X$ can be calculated in the following steps:

1) Set $k = 0.0092$, get symbol sequence S from X using Equation (2).

2) Set $m = 2$, get the constructed symbol sequence S' using Equation (4). Since $m = 2$, every vector in S' should be one of the 16 modes, 00, 01, 02, 03, 10, 11, 12, 13, 20, 21, 22, 23, 30, 31, 32 and 33.

3) For every mode, calculate its frequency of occurrence, that is probability p_i, $i = 1, \cdots, 16$, using Equation (5).

4) Calculate $SIE(m)_X$ using Equation (6).

Take the first day SCR signal of no emotion state as an example, the probabilities of 16 modes are $p_{00} = 0.1571$, $p_{01} = 0.0005$, $p_{02} = 0$, $p_{03} = 0.0055$, $p_{10} = 0.0005$, $p_{11} = 0.0030$, $p_{12} = 0$, $p_{13} = 0$, $p_{20} = 0$, $p_{21} = 0$, $p_{22} = 0.0030$, $p_{23} = 0.0005$, $p_{30} = 0.0055$, $p_{31} = 0$, $p_{32} = 0.0005$ and $p_{33} = 0.8239$. Its symbolic information entropy is $SIE(2) = 0.8046$.

Since we know the probabilities of 16 modes of every SCR signal in the third step, we can get the mean probabilities of 16 modes of 20 days for each emotion, as shown in Fig. 2. We can see that the continuous slowly increasing mode (00), continuous fast increasing mode (11), continuous fast decreasing mode (22) and continuous slowly decreasing mode (33) are dominant, and the probabilities of 11 mode and 22 mode are smaller than 00 mode and 33 mode. The SCR signal changes slowly most of the time, slowly increasing or slowly decreasing. Fast increasing and fast decreasing are relatively less. This is in accordance with the response pattern of SCR. That is, when stimuli event occurs, the skin conductance rise immediately and then has biphasic decay,

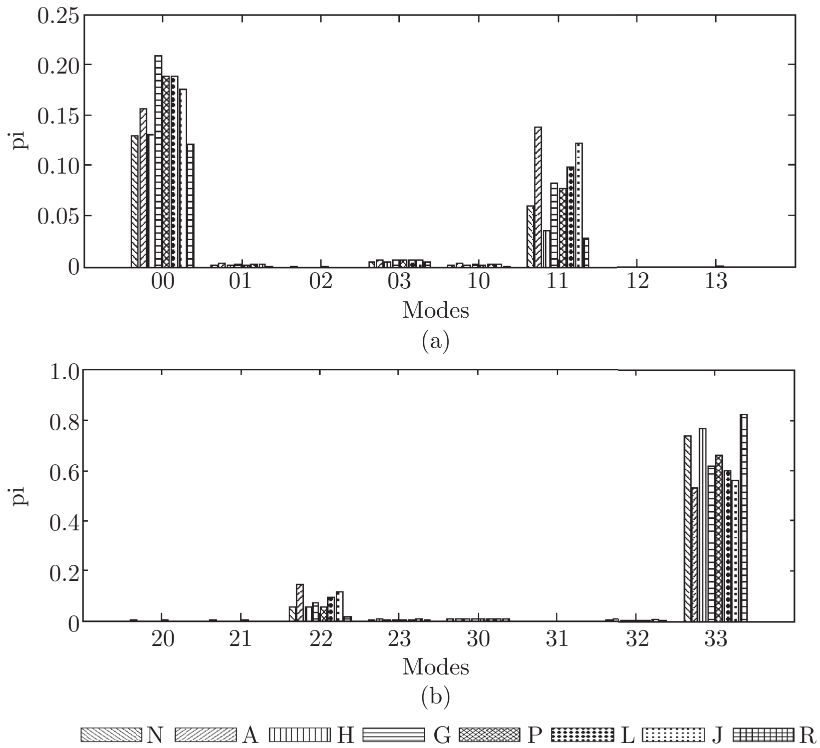

Fig. 2: Mean probability of 16 modes of eight affective states, (a) shows mode 00 to 13 and (b) shows mode 20 to 33. The x axes of (a) and (b) show the 16 combinations (modes) of the four symbols 0-slowly increasing, 1-fast increasing, 2-fast decreasing and 3-slowly decreasing, and the y axes show the mean probabilities of each mode in SCR symbolic sequences of each affective state. Eight affective states from left to right: no emotion, anger, hate, grief, platonic love, romantic love, joy and reverence

first fast decreasing and then slowly decreasing (Fig. 1). This biphasic response is predicted by the qualitative pore valve model [26], where the steep rise and fall of the skin conductance are caused by rapid opening and closing of sweat duct pores, while a slower recovery is affordable by evaporation of remaining sweat from the skin.

Among the eight affective states, the probabilities of 11 and 22 modes of anger are biggest, which means there are many fast skin conductance changes in anger state. Next is joy and romantic love. The probabilities of 11 and 33 mode of reverence are relatively large, implying the sympathetic nerve activity was suppressed, and the fluctuations of skin conductance response were moderate. In addition, the probability distribution of no emotion and hate, grief and platonic love are similar, so the affective state in these two group emotions may have a similar skin conductance response pattern respectively.

Symbolic information entropy can be used to quantitatively describe the irregularity of fluctuation patterns of SCR signals. The distribution of SIE of SCR signals of eight affective states can be see in Fig. 3, the mean SIE of the eight affective states arranged in descending order are: anger, joy, romantic love, grief, platonic love, no emotion, hate and reverence. We know the arousal level of the subject's feeling of each affective state from Table 1, and compare it with the mean SIE of each affective state in order to observe the relationship between arousal level and SIE. The comparison is shown in Fig. 4, the upper image is the arousal level the subject's feeling and the lower image is the mean SIE of each affective state. From Fig. 3 and 4, we can see that, SIE is inconsistent with the arousal level of the subject's feeling in general. For example, the subject felt calm and peace in reverence state, and the arousal level is very low, which corresponds with the mean SIE of her SCR, the lowest in the eight affective states. The arousal level of platonic love of the subject is low, same as no emotion and hate, but the mean SIE is much higher than that two emotion states. We suspect that the imagery about family and summer brought much happiness than the subject thought. The mean SIE of platonic love, however, is lower than other high arousal affective states. We also observed the relationship between emotional valence and SIE and there is no evidence of a correlation between them.

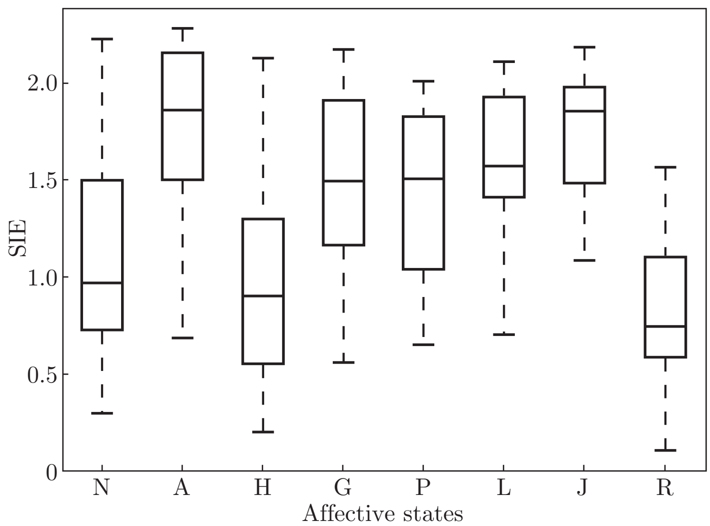

Fig. 3: The distribution of SIE of eight affective states

To investigate further, the SIE of eight affective states were analyzed by one-way ANOVA [27]. The ANOVA tested the null hypothesis that samples in two or more groups are drawn from

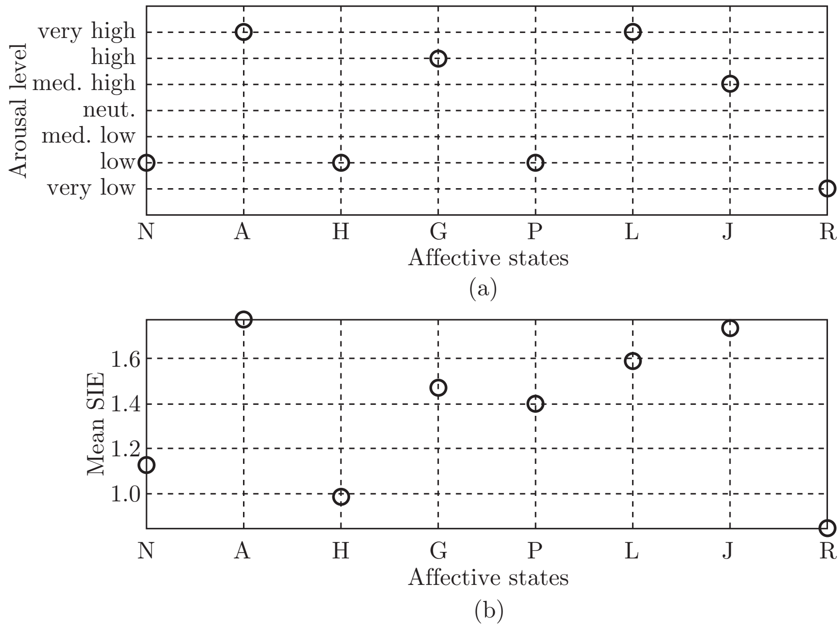

Fig. 4: Comparison between the arousal levels from the subject's report and the mean SIE of each affective state. (a) shows the arousal level of the subject and (b) shows the mean SIE of each affective state

populations with the same mean values. If the test score P values are lower than the significant level 0.05, we should reject the null hypothesis, and that means the fluctuation patterns of the SCR signals of two affective states are different. If $P \leq 0.05$, the difference is significant, and if $P \leq 0.01$ the difference is very significant. The P values of each pair of emotions were calculated by anova1 function provided by MATLAB and the test results are shown in Table 2. In general, higher SIE reflects higher emotional arousal level in contrast with the subject's self-report of the arousal level of each emotion. Anger and Joy have no significant difference with each other and

Table 2: ANOVA test result of SIE of each pair Affective States

	N	A	H	G	P	L	J	R
N	n.s.	**	n.s.	*	n.s.	**	**	n.s.
A	**	n.s.	**	*	*	n.s.	n.s.	**
H	n.s.	**	n.s.	**	*	**	**	n.s.
G	*	*	**	n.s.	n.s.	n.s.	*	**
P	n.s.	*	*	n.s.	n.s.	n.s.	**	**
L	**	n.s.	**	n.s.	n.s.	n.s.	n.s.	**
J	**	n.s.	**	*	**	n.s.	n.s.	**
R	n.s.	*	n.s.	**	**	**	**	n.s

Note: The n.s. means there is no significant difference between the two affective states ($P > 0.05$), * means there is significant difference between the two affective states ($P \leq 0.05$) and ** means there is very significant difference between the two affective states ($P \leq 0.01$).

romantic love but have significant difference with the other five emotions, and therefore, they are at the same arousal level. Romantic love not only has no significant difference with anger and joy but also with grief and platonic love, and its mean SIE lies between this two groups, so its arousal level is in the middle of the two groups. Grief and platonic love have no significant difference with each other and romantic love, but have significant difference with anger, joy, no emotion, hate and reverence, so they are at the same arousal level. No emotion has no significant difference with hate and reverence and meanwhile has no significant difference with platonic love. The mean SIE of no emotion lies between that of platonic love and hate, so the arousal level of no emotion is in the middle of hate and platonic love. Since hate and reverence have no significant difference with each other but have significant difference with the other five emotions, they are at the same arousal level. The eight emotions can be divided into three groups as a whole, high, medium and low arousal levels. The high arousal level group includes anger and joy, the medium arousal level group includes romantic love, grief and platonic love, and the low arousal level group includes no emotion, hate and reverence. The result is in accordance with the arousal effect obtained using musical excerpts or slides of affective pictures when environmental sounds were employed [1, 28].

5 Discussion

Due to the fact that traditional time-domain analysis methods do not consider the timing and structure of the sequence, such complex and nonlinear methods in the study of SCR signal gain widespread attention. Conventional nonlinear parameters such as correlation dimension and Lyapunov exponent calculation required large amount of data [29], when the SCR signal analysis applied to signal acquisition takes an hour or even longer, inconvenient for online use, so the study of short-time analysis method was highly valued. Approximate entropy [30] (ApEn) is widely used in signal complexity analysis in recent years, and has been suggested to measure the complexity of short data sets. ApEn reflects the increases of the possibility of a new mode when the dimension increased. Greater ApEn means larger opportunity of a new mode, and stronger irregularity of the signal. We calculate ApEn of SCR signals of eight affective states by MATS toolkit [31]. ApEn has four input parameters, they are X, m, τ and r. X is the SCR signal, m specifies the embedding dimension, $\tau$is the delay time and r defines the criterion of similarity. According to [30], we set $m = 2$, $\tau = 1$ and $r = 0.2 * std(X)$. The $std(X)$ is the standard deviation of X. Fig. 5 shows the distribution of ApEn of SCR signals of eight affective states, and we can see that, the distribution of ApEn looks similar with the distribution of SIE. The mean ApEn of the eight affective states which arranged in descending order are: anger, joy, romantic love, no emotion, grief, platonic love, hate and reverence. The comparison between arousal levels of the subject and the mean ApEn of each affective state is shown in Fig. 6.

From Fig. 5 and 6, we can see that, although high arousal emotions such as anger and joy have higher ApEn than other affective state, the mean ApEn of high arousal emotion grief is lower than the low arousal state of no emotion. In comparison, the mean SIE have better consistency with the arousal level of the subject. In addition, the symbolic information entropy is conceptually simple and computationally very fast. The two parameters of SIE are easy to determine while choosing appropriate parameters for ApEn needs a lot of work [14]. These characteristics determine the practical value of symbolic information entropy, and it can also be applied to other physiological signals, or other areas of the complex signal analysis.

Valence and arousal represent the most commonly identified in dimensional theories of the

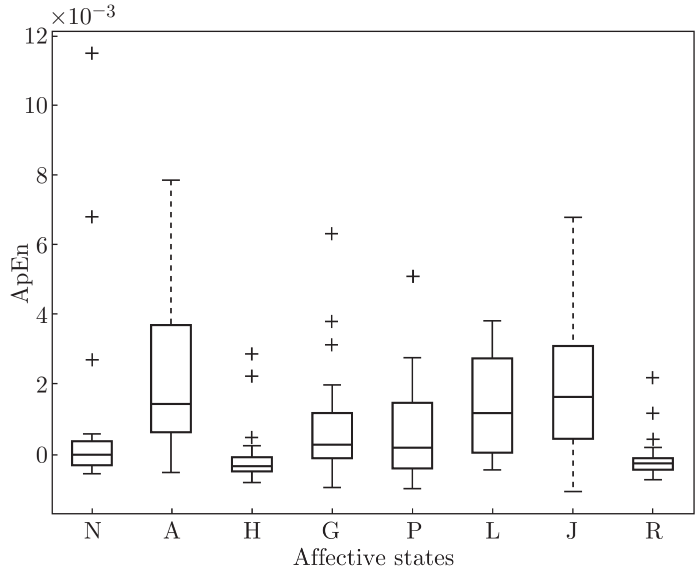

Fig. 5: The distribution of ApEn of eight affective states

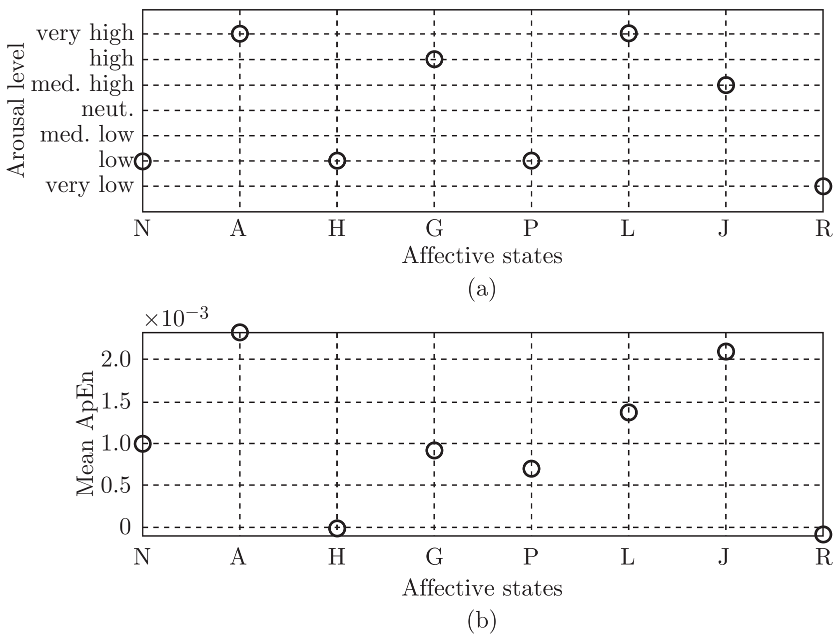

Fig. 6: Comparison between the arousal levels from the subject's report and the mean ApEn of each affective state. (a) shows the arousal level of the subject and (b) shows the mean ApEn of each affective state

psychology of emotion [32, 33]. Emotional valence describes the extent of pleasure or sadness and emotional arousal describes the extent of calmness or excitation. SCR is an indicator of the alterations in the sympathetic branch of ANS, which innervate the secretory of the sweat gland. The intensity of skin conductance responses is always related to stimulus intensity and/or its psychological significance [2]. Therefore, measuring the complexity of the fluctuations of SCR signals recorded in different affective states show intensify and frequency of the emotion-inducing events. The symbolic information entropy was proposed and applied to measure the irregularity of the fluctuations of SCR signals. We use four symbols that indicate the SCR signal fluctuations (slowly increasing, fast increasing, fast decreasing and slowly decreasing). Configure the SCR symbolic sequence to a certain window width in order to reflect the timing and structure of various modes through the statistical probability distribution. Calculate symbolic information entropy to quantify the complexity of the SCR induced by different emotional events, and then discuss the SC emotional response patterns from arousal and valance dimensions. The results show that the mean SIE of eight affective states is basically in accordance with the arousal level of the subject's self-report. According to SIE, the arousal levels of eight affective states in a descending order as: anger, joy, romantic love, grief, platonic love, no emotion, hate and reverence. Platonic love is lower than the subject's self-report and joy is higher than self-report. In general, high arousal emotion makes people more excited, and keeps their mind active, that result in high frequency and intensify stimuli and consequently high irregular fluctuations in SCR signal. The low arousal emotion, such as reverence, makes people calm and in a peaceful state, and therefore the variation of the skin conductance is gentle. Emotional valence has no correlation with SIE, for example, both positive state joy and negative state anger have large SIE. There is no statistical difference between positive emotions and negative emotions. SCR is more sensitive to variations in emotional arousal rather than in valence.

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