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A spatial filtering approach to environmental emotion perception based on electroencephalography

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A B S T R A C T

Studies have demonstrated that visual built environments can affect the emotions of individuals, which can be recorded and investigated using electroencephalography (EEG). To study emotional intensity in adolescents exposed to different visual built environments, we proposed an EEG-based spatial filtering method using Independent Component Analysis (ICA). Specifically, to identify effective video stimuli to induce emotions, we first developed a stimulus selection strategy using the normalized valence/arousal space model. Subsequently, we designed an optimum ICA-based spatial filter by analyzing independent component-to-electrode mapping patterns in different emotional states. Based on this, EEG signals with five emotional intensities in terms of arousal and valence dimensions were linearly projected by the designed filter to extract feature parameters. Finally, we used the Support Vector Model as the classifier to recognize emotions. In the laboratory environment, the average recognition accuracy ratios for the valence and arousal dimensions were 73.35% and 68.54% (within-participant test) and 66.98% and 62.62% (between-participant test), respectively, for the 10 participants. The experimental results validated the feasibility of the proposed ICA-based spatial filtering algorithm for emotional intensity recognition.

1. Introduction

Studies have shown that psychological problems have increased significantly among Chinese adolescents in recent years [1,2]. According to conservative estimates, 30 million children and adolescents have different psychological problems [1], and 16.0–25.4% of undergraduate students have mental disorders such as anxiety, neurotic behaviors, neurasthenia, and depression [3]. Moreover, these psychological problems have a trend to increase in prevalence at present. The World Health Organization predicted that the number of adolescents with neuropsychological problems will increase worldwide by more than 50% by the year 2020. At this time, neuropsychological problems would become one of the top five conditions leading to disease, disability, and even death for adolescents [4]. The visual environment has been proven to alter emotions and affect mood [5] . Different living environments would therefore have different impacts on the emotional and psychological health of adolescents. For instance, an adolescent may feel excitement (i.e., a high level of arousal) when he or she is in a bustling or noisy space. However, a high level of arousal for a long duration would lead to fatigue, which is harmful to health [6]. In contrast, quiet green spaces or landscapes can effectively relax one's mood and decrease emotion arousal, as green spaces have been shown to be restorative environments [7–10]. Thus, it is crucial to investigate adolescents' emotional perceptions in different visual built environments for scientific prevention and effective control of psychological problems.

Electroencephalography (EEG), which is a type of bio-signal generated by the brain activities and can be recorded using non-invasive techniques, has been shown to provide more relevant emotional information than peripheral bio-signals (e.g., electrocardiography [ECG], electrooculography [EOG], electromyography, skin conductance, and respiration) [11–13]. EEG has thus become a research tool for emotion recognition. For example, Lin et al. [14] investigated the relationships between emotional states and brain activities. They extracted data regarding power spectrum density, differential asymmetry power, and rational asymmetry power to categorize emotional EEG signals. Petrantonakis and Hadjileontiadis [15] used higher order crossings data as emotional features to classify six basic emotions, i.e., happiness, surprise, anger, fear, disgust, and sadness. Murugappan et al. [16] used discrete wavelet transforms in the alpha, beta, and gamma frequency bands to iden-

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tify content-induced emotions based on EEG data. Atkinson and Campos [17] used the Minimum-Redundancy-Maximum-Relevance algorithm to choose the features that most strongly correlated with the emotional classification variable. The methods have mainly focused on the time/frequency analysis of emotional EEG signals, while spatial information from emotional nerve "sources", which can be used to clearly distinguish different emotional tasks, have been ignored. Additionally, the emotions studied in the previous reports were generally induced by specific stimuli, and there are few reports regarding environmental emotional perception, which plays an important role in mental health diagnosis, psychological rehabilitation, etc.

Aiming to address the above problems, we proposed a spatial filtering algorithm based on Independent Component Analysis (ICA) to process emotional EEG signals on both the arousal and valence dimensions in order to investigate environmental psychological perception in adolescents. The main contributions of our study are (1) application of ICA algorithm to establish a spatial filter bank and extract spatial features according to different emotional states, (2) design of an Emotion-Related Independent Components (ERICs) automatic selection and validity judgment method based on the relationship between emotional states and scalp maps, and (3) development of a dual model including a valence sub-model and an arousal sub-model to synchronously assess emotional intensity in two dimensions.

2. Materials and methods

2.1. Data preparation

2.1.1. Stimuli selection

We used a total of 150 original video clips lasting 3–5 min. Ninety of these clips were recorded in different visual built scenes and the rest were collected from movies. In order to guarantee the validity of emotional induction, we carefully selected the stimuli using the following steps.

In general, if the duration of a stimulus video was too long, different emotional elicitation information was included in the same video clip. As a result, the data labels would not consistent with the collected EEG data. This would have led to reduce recognition performance. In contrast, if the duration of a video was too short, the desired emotion could not be induced sufficiently. To ensure effective elicitation of a single emotion, we first used clips that were as short as possible to avoid multiple emotions. We thus manually extracted 55-s highlighted video segments with maximum emotional content from each of the original stimuli. We then preliminarily selected 100 test clips from the 150 highlighted videos using a self-assessment software developed in our laboratory. Using this software, the participants could use the mouse to click on different check-boxes to express their emotional responses after viewing a stimulus video. A screenshot of the self-assessment software is shown in Fig. 1.

Furthermore, to determine the emotional intensity in response to the different built environments, we non-linearly scaled the emotions into five levels based on the arousal and valence intensities, i.e.,

- Arousal: low arousal (level 1), low-medium arousal (level 2), medium arousal (level 3), medium-high arousal (level 4), high arousal (level 5);
- Valence: low valence (level 1), low-medium valence (level 2), medium valence (level 3), medium-high valence (level 4), and high valence (level 5).

On this basis, we further chose the most representative 40 stimuli from the 100 optimized test clips to improve our assessment of the induced effect. Specifically, we first displayed the stimuli

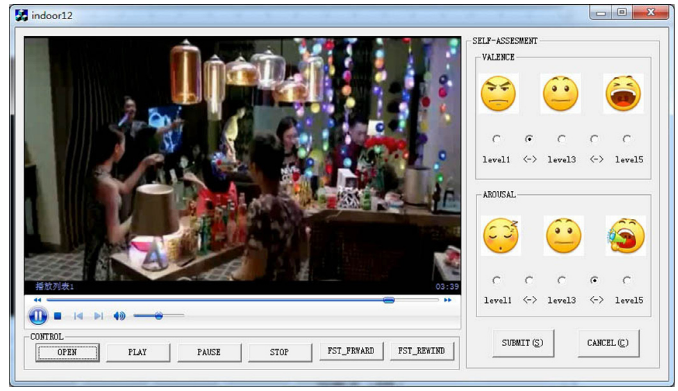

Fig. 1. A screenshot of the self-assessment software. The label "VALENCE" indicates the preference associated with the negative or positive situation, which ranged from unpleasant to pleasant. The label "AROUSAL" indicates the intensity of excitement (from calm to excited) in response to sensory stimulation. The options "level 1" to "level 5" are used to denote the emotional intensity from the lowest level to the highest level. "Level 3" indicates the neutral emotional state.

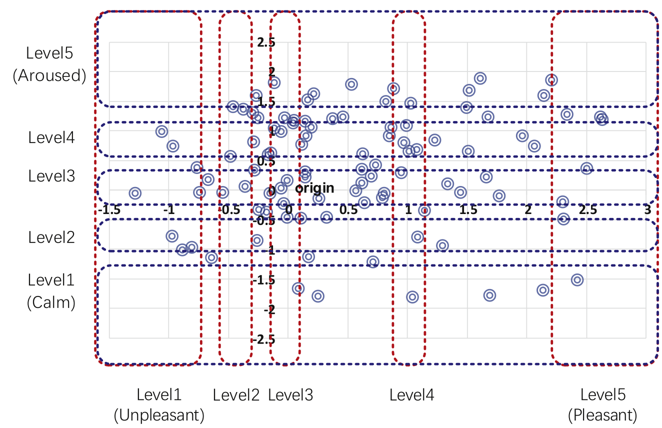

Fig. 2. Illustration of the method used to select the stimuli based on the normalized 2-D valence/arousal space model. The total number of videos is 100 and the blue points indicate the score value for each video. The horizontal axis denotes the arousal dimension and the red rectangles denote the scopes of the five levels on the arousal dimension. Similarly, the vertical axis represents the valence dimension and the blue rectangles denote valence intensity. We ultimately selected 40 (5 levels * 8 videos per level) videos that represented an emotional state on each dimension. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

videos at random and asked each participant to watch the stimuli as many times as he/she desired. We then computed the normalized arousal and valence score, x, for each stimulus video using the following equation:

$$score(x) = \frac{\mu_x}{\sigma_x} \tag{1}$$

where μ_x is the mean rating and σ_x represents the standard deviation. The stimulus selection method used is shown in Fig. 2.

As seen in Fig. 2, some extreme emotional states are seldom induced because the story plots are not presented in visual built environments. As a result, the number of stimulus videos located in the low valence and high arousal region is less than that for other regions. Based on the distribution of the stimuli, we selected 5 representative areas on each dimension of the 2-D model and determined 8 optimum sample points as training data in each area, that is:

- On the arousal dimension: 8 training stimuli that were closest to the origin (red point shown in Fig. 2) on the horizontal axis were chosen as level 3 stimuli; stimuli that were closest to 2.5

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