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Emo-regulator: An emotion-regulation training system fusing virtual reality and EEG-based neurofeedback

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***Abstract*—Good emotion-regulation ability (ERA) is a vital sign of psychological health; conversely, emotion dysregulation may lead to mental or neurological disorders, such as anxiety disorders and depression. This study developed an emotion-regulation training system, Emo-regulator, fusing virtual reality (VR) and EEG-based neurofeedback to enhance subjects' ability to down-regulate negative emotions. Emo-regulator first elicited negative emotions in subjects through VR scenarios and then asked them to regulate emotions using cognitive reappraisal to change the emotional responses elicited by the VRs. Meanwhile, EEG signals from the subjects were collected and analyzed in real time by machine learning to predict the emotional states of the subjects (negative or positive). Emo-regulator changed the VR scenarios according to the prediction results and completed the feedback. Eight subjects used Emo-regulator for two weeks, and the results showed it could help the subjects improve their emotion regulation, and its usability is above average.**

***Clinical Relevance*—Emo-regulator can help subjects improve their ability to down-regulate negative emotions and increase the frequency of cognitive reappraisal use during emotion regulation.**

I. Introduction

Emotion regulation is the ability to recognize emotions and control the intensity and duration of emotional experiences [1], an important cognitive function that allows humans to adapt to their environment. Good emotion-regulation ability (ERA) is a vital sign of psychological health [2]; conversely, emotion dysregulation may lead to mental or neurological disorders [3], such as anxiety disorders and depression. Also, some physical illnesses may be accompanied by emotion regulation difficulties. Taking coronavirus disease 2019 (COVID-19) as an example, the United Nations, as early as May 2020, issued a policy brief, "Mental health services are an essential part of all government responses to COVID-19", which states that "Even when the pandemic is brought under control, grief, anxiety and depression will continue to affect people and communities" [4]. Therefore, developing a practical approach to improving people's ERA is imperative.

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Electroencephalography (EEG)-based neurofeedback, a type of biofeedback featuring the benefits of non-invasiveness, low cost, and ease of use, has become an innovative tool in teaching brain self-regulation, including emotion regulation [5]. Most emotion-regulation training systems based on EEG neurofeedback use two-dimensional (2D) pictures or videos as mood induction procedures (MIPs) to elicit specific emotional states in subjects. For example, Huang et al. [5] developed a brain-computer interface (BCI) system based on real-time EEG neurofeedback to improve subjects' emotion regulation. Their system runs in two phases: calibration and training. In the calibration phase, EEG features of the subjects during the viewing of positive, neutral, and negative videos were extracted and fed into a support vector machine (SVM) to create an emotion classifier; while in the training phase, the subjects were asked to modulate their emotions to positive, neutral or negative states and are informed by the trained SVM whether the emotion regulation is successful. Twenty subjects used their system, each completing 10 training sessions over 5 weeks, and the results showed a significant increase in ERA after the training compared to before the training. Arpaia et al. [6] developed an emotion-regulation training system taking 2D pictures from the International Affective Picture System (IAPS) as MIPs and used a virtual reality (VR) headset to display the pictures to the subjects. Although they used a VR display system, the contents were still 2D pictures. These 2D videos and pictures lack interactivity and the information of depth compared to scenes in an actual three-dimensional (3D) world. Moreover, previous research has shown differences in activation patterns between the brain when processing 2D and 3D information [7], which may lead to unsatisfactory results when applying these studies to the real world.

In this work, we developed an EEG-feedback emotion-regulation training system, Emo-regulator, to improve the subjects' ability to down-regulate negative emotions. Unlike previous studies, we used 3D VR as MIPs, which allows for simulating the natural world in a controlled laboratory environment.

II. Materials and Methods

A. System architecture

Emo-regulator aimed to enhance subjects' ability to down-regulate negative emotional responses, which contains the following major modules: VR stimuli, EEG acquisition, EEG pre-processing, EEG feature extraction, and emotion recognition and feedback. The workflow of these modules is shown in Figure 1. From Figure 1, a typical emotion regulation process is as follows:

(a) Presenting subjects with negative VR scenarios to elicit their negative emotions, then asking them to regulate emotions using cognitive reappraisal to change the emotional responses evoked by the scenarios. We ask the subjects to use cognitive reappraisal during emotion regulation because it is healthier, more effective, and does not impair memory compared to another commonly used regulation strategy, expression suppression [8].

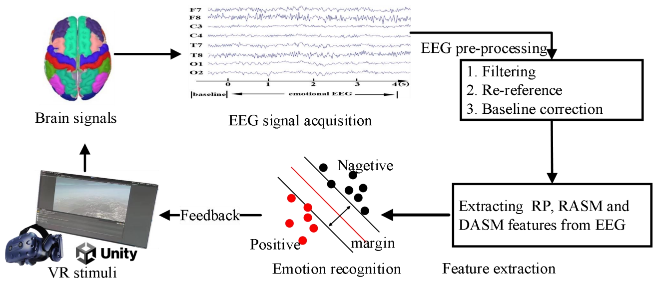

Figure 1. The workflow of Emo-regulator.

(b) Collecting subjects' EEG from 8 electrodes (F7, F8, T7, T8, C3, C4, O1, and O2) distributed through frontal, temporal, parietal, and occipital regions.

(c) Pre-processing the collected EEG to minimize the effect of artifacts.

(d) Extracting relative power (RP), inter-hemispheric power rational asymmetry (RASM), and differential asymmetry (DASM) indices from the pre-processed EEG, then concatenating and feeding them into a pre-trained SVM-based emotion classifier to determine the real-time emotional states of the subjects (negative or positive).

(e) Adjusting the presented VR scenarios according to the predicted emotional states every 4 seconds to let the users perceive their dynamic changes.

When the subjects' emotional states are detected to be positive, the round of regulation ends and goes to step (a) for a new regulation. Next, we will introduce the details of each module implementation.

B. *Module implementation*

(1) VR stimuli

Eight 3D VR scenarios (4 positives and 4 negatives) were developed using the Unity2019 engine to induce positive and negative emotions. Materials used to construct the scenarios were obtained from the Unity Asset Store. An HTC Vive headset was used as a display device for the VR scenarios. Figure 2 provides snapshots of a negative scenario and a positive scenario.

(a) billowy sea (b) sunny sea

Figure 2. Snapshots from a negative (billowy sea) and a positive (sunny sea) scenario.

(2) EEG acquisition

EEG signals were collected using a wireless EEG system (Neuracle NSW308), which has 8 channels located in the frontal (F7 and F8), parietal (C3 and C4), temporal (T7 and T8), and occipital (O1 and O2). We chose an 8-channel EEG device to reduce the experiment preparation time. For example, a 64-channel EEG device may take more than 30 minutes to apply the conductive paste, which is a significant burden for both the operator and the subjects. In addition, according to our previous study [9], the EEG features from a few electrodes located in the frontal and occipital can well distinguish between different emotional states.

EEG data collected by the NSW308 needed to be transferred to Emo-regulator. We deployed the NSW308 recorder and Emo-regulator on the same local area network (LAN); both were connected via Wi-Fi (physical layer and data link layer) and used TCP/IP socket to transfer EEG data between them (network layer and transport layer). Figure 3 is the Unified Modeling Language (UML) timing diagram of the data transfer between them.

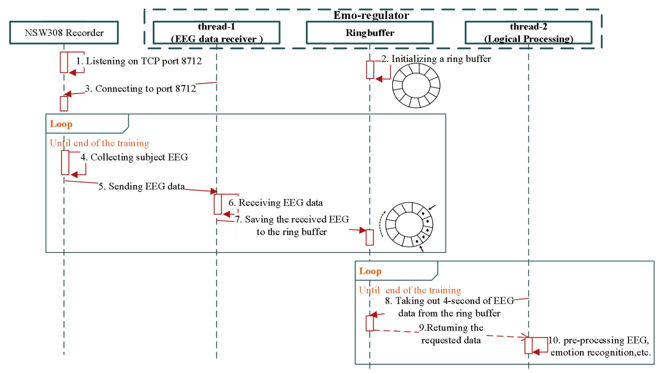

Figure 3. UML timing diagram of EEG data transfer between the NSW308 recorder and Emo-regulator.

As shown in Figure 3, NSW308 Recorder is the EEG recording software, listening on TCP port 8712. Emo-regulator forks two threads: thread-1 and thread-2. The thread-1 initializes a ring buffer and establishes a long TCP connection with port 8712 of NSW308. It receives EEG data sent by NSW308 Recorder and stores the received data in the ring buffer. The thread-2 is responsible for the logical processing of EEG data. It takes 4 seconds of EEG data from the ring buffer each time for further pre-processing, feature extraction, and emotional state recognition.

(3) EEG pre-processing

Emo-regulator's logical processing thread (thread-2, as shown in Figure 3) takes 4 seconds of EEG data from the ring buffer each time. Then the 4 seconds of EEG data will be passed through a 50 Hz notch filter to remove the line noise and a 0.1-60 Hz band-pass filter. For the filtered data, a 1-second resting-state EEG is spliced in front of it as a baseline, followed by EEG re-reference and baseline correction.

(4) Feature extraction

Emo-regulator first divided the pre-processed EEG data by a fourth-order Butterworth filter into four sub-frequency bands of interest (i.e., theta, 3-7 Hz, alpha, 8-13 Hz, beta, 14-29 Hz, and gamma, 30-47 Hz), and then calculated the RP, DASM, and RASM for each frequency band. Here, we briefly described the definitions of RP, DASM, and RASM.

Relative power reflects the percentage of a given frequency band power compared to total frequency band power, which can diminish inter-individual variation in contrast to absolute power. To calculate the RP of a specific sub-frequency band in a time series x, the following method can be used: [9]

(a) Calculating power spectral density (PSD) for the time series x using the Welch periodogram method with the Hanning window. Welch's method involves dividing the time series x into L segments, each containing K data points, computing the periodogram for each segment, and then averaging them.

(b) Calculating the absolute power for the sub-frequency band by estimating the area under the sub-frequency PSD curve using Simpson's rule.

(c) Calculating the ratio of the sub-frequency band absolute power to total bandwidth absolute power:

$$\mathrm{RP} = \frac{\text{absolute power of the sub-frequency band}}{\text{absolute power of total bandwidth}}. \qquad (1)$$

For the inter-hemispheric power asymmetry indices, four asymmetry indices result from four symmetric electrode combinations, namely F7-F8, C3-C4, T7-T8, and O1-O2. The power asymmetry indices can be computed using either relative power division or subtraction, as specified in formulas (2) and (3).

$$\mathrm{RASM} = \mathrm{RP(left)}/\mathrm{RP(right)} \qquad (2)$$

$$\mathrm{DASM} = \mathrm{RP(left)} - \mathrm{RP(right)} \qquad (3)$$

We extracted the EEG power spectrum as features, mainly considering its high classification accuracy [9] and its stability over time compared to coherence, entropy, etc. [10].

(5) Emotion recognition and feedback

Before the emotion regulation training, Emo-regulator collected EEG data from the current subject in positive and negative emotional states (using the 8 VR scenarios from the VR stimuli module as MIPs) and merged them with our previously developed VR emotional EEG dataset [9] to train an SVM classifier for emotion recognition. The extracted EEG features by the feature extraction module will be combined and fed into the pre-trained SVM classifier to predict the subjects ' real-time emotional state (negative or positive). The prediction results will be written to a Redis database [11] and then feedback to the VR stimuli module through the Redis publish/subscribe mechanism. Subsequently, the VR stimuli module will adjust the presenting VR scenario according to the feedback emotion. Taking Figure 1 as an example, when the subject's emotion changes from negative to positive, the VR stimuli module turns the size and color of the waves, changing from a billowy sea to a sunny sea.

In the implementation processes of the above modules, we developed the VR stimuli module using the Unity2019 engine and programming with C# language. Other modules were implemented with Python language and depended on open-source Python packages such as neuracle_lib, MNE-Python, Scikit-learn, etc.

C. *Subjects and Procedures*

Eight healthy college students (4 males and 4 females, mean age of 24.3 ± 3.5 years) from Shanghai University were recruited and used Emo-regulator to improve their ability to down-regulate negative emotions (Figure 4). Each subject was asked to complete 6 training sessions of emotion regulation over two weeks, with the time of two adjacent sessions separated by >24 hours and the duration of each session approximately 20 minutes. The subjects were asked, before and after training, to complete the emotion regulation questionnaire (ERQ), the difficulties in emotion regulation scale (DERS-16), the Rosenberg self-esteem scale(RSE) scale, and the hospital anxiety and depression (HADS) scale to assess the changes in ERA, and after the training, complete the system usability scale (SUS) to determine the usability of Emo-regulator itself.

Figure 4. Photograph of a subject undergoing emotion regulation training.

III. Statistical tests

We used paired-sample t-tests to measure the score differences in ERQ, DERS-16, RSE, and HADS before the first training and after the last training session, with a significance level taken as 0.05. For the SUS scale, we calculated the mean of all subjects' scores to assess the usability of Emo-regulator itself.

IV. Results

Seven of the eight subjects completed 6 training sessions, and the other subject completed 5 sessions due to the effects of COVID-19.

The ERQ is designed to assess individual differences in the habitual use of two emotion regulation strategies: expressive suppression and cognitive reappraisal. Figure 5 shows the ERQ scores before the first training session and after the final training session.

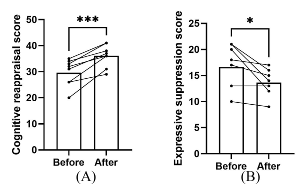

Figure 5. ERQ scores before and after training for the (A) cognitive reappraisal and (B) expressive suppression (* indicates p<0.05 and *** p<0.001).

From Figure 5, after training, the cognitive reappraisal scores were significantly higher, whereas the expressive suppression scores were lower, indicating that subjects increased cognitive reappraisal and decreased expression suppression during emotion regulation. Considering that cognitive reappraisal is healthier and more effective than expressive suppression [8], we asked subjects to use cognitive reappraisal during the training, which may lead to a shift from expressive suppression to cognitive reappraisal.

The DERS-16 scale measures emotion regulation problems, with a higher DERS-16 score indicating greater difficulties in emotion regulation. Figure 6 shows the DERS-16 scores before and after training.

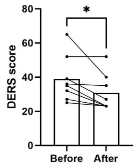

Figure 6. DERS-16 scores before and after training (* indicates p<0.05).

From Figure 6, the DERS16 scores were significantly lower after training, indicating an increase in overall ERA.

The DERS-16 can be further divided into five subscales involving: nonacceptance, goals, impulse, strategies, and clarity to assess difficulties in emotion regulation from five dimensions. Subjects' scores on the five subscales before and after training are shown in Figure 7.

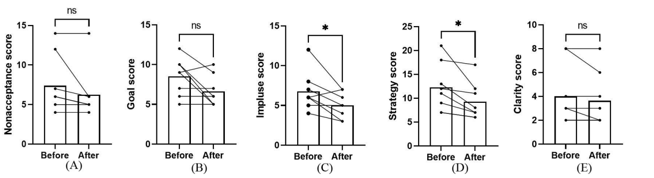

Figure 7. Five subscale scores of DERS16 before and after training for the (A) nonacceptance, (B) goal, (C) impulse, (D) strategies, and (E) clarity (ns indicates p>0.05 and * indicates p<0.05).

From Figure 7, the scores of impulse (difficulties controlling impulsive behaviors when distressed) and strategies (limited access to emotion regulation strategies perceived as effective) decreased significantly after training, indicating that the subjects' emotion regulation ability improved mainly in these two dimensions.

The RSE measures overall self-worth by measuring positive and negative feelings about the self. The RSE scores before and after training are shown in Figure 8.

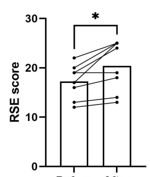

Figure 8. RSE scores before and after training (* indicates p<0.05).

From Figure 8, the RSE score after training is significantly higher than before, indicating a higher level of self-esteem after training.

The HADS is mainly applied to screen for anxiety and depression in general hospital patients. Figure 9 shows the anxiety and depression scores of the subjects before and after training sessions.

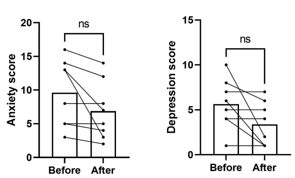

Figure 9. Anxiety and depression scores of the HADS before and after training (ns indicates p>0.05).

From Figure 9, although the subjects' depression and anxiety decreased, they were not statistically significant (or only marginally significant (p<0.1)), with p-values of 0.06 for anxiety and 0.07 for depression.

The SUS offers a quick yet accurate way to evaluate the usability of software systems. The average SUS score of Emo-regulator was 69.84 ± 2.95 (Figure 10), indicating Emo-regulator's above-average usability (SUS>68)[12].

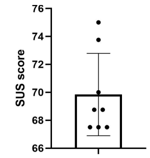

Figure 10. Average SUS score (error bar denotes standard deviation).

From the abovementioned results, the subjects, after training, were more inclined to use cognitive reappraisal to regulate their emotions, and their ERA and self-esteem level improved. In addition, the usability of Emo-regulator was also above average level.

V. CONCLUSION

In this paper, we developed an emotion regulation system based on EEG neurofeedback, Emo-regulator, which used 3D VR as MIPs. The results showed Emo-regulator could help subjects improve emotion regulation, and its usability was above average. The future work is to apply Emo-regulator to a larger number of subjects from different age groups in order to enhance their down-regulating ability for negative emotions.

The experimental procedures involving human subjects described in this paper were approved by the Ethics Committee of Shanghai University (Approval No. ECSHU 2021-224) and adhered to the Declaration of Helsinki.

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