User-centered Depression Prevention: An EEG approach to pervasive healthcare

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***Abstract*-There have been a number of research projects which have addressed depression, the focus often being on aspects of pharmacology and psychology. Relatively few of the investigations have tried to integrate depression and the related issues into a pervasive depression prevention system incorporating user-centered design. In this paper we propose an approach to provide relief for a user(s) depression by implementing a personalized treatment program; this is implemented in an electroencephalogram (EEG) based music therapy system. EEG plays two roles in this approach: to identify the user (a critical factor in achieving personalized service provision) and to measure the degree of depression. This paper considers the methodology of our EEG approach with design parameters for each component in a pervasive environment. The experiments involved 22 subjects and 4 subjects respectively in user identification and depression detection to evaluate the EEG approach. The results reported are positive and support the conclusion that the EEG approach provides an effective approach to user-centered depression prevention Additionally, the research outcomes support the conclusion that a mobile music therapy system offers beneficial effects for the treatment of depression. The paper concludes with a brief discussion on challenges, outstanding research questions, and future work.**

Keywords- EEG; Depression Prevention; User-centered; Pervasive

I. INTRODUCTION

In today's rapidly evolving society, the incidence of mental disorder(s) is an issue of growing importance. Within the range of mental disorders depression represents a significant and growing subset [of the mental disorder landscape]. In fact, it has been estimated that approximately 25% of the world's population will experience episodes of depression during their life time (WHO). Additionally, while there are a number of drugs to treat depression, fewer options are provided for prevention of depression. There is an urgent need for the development of a pervasive depression prevention system incorporating personalized service provision.

In the past, almost all the results [of an individual psychological state] are derived from ethnographic research often using patients' questionnaires. In this way, results of the investigations may be subjective and can be in question. This is due to the sensitivity of mental change [1]. Objective and precise measurement of depression is termed EEG and has been introduced to: (1) measure physiological and psychology correlations, and (2) to reflect depression levels [2] and individual identity [3-7]. These selection of these options represent a significant issue. In our system, EEG plays two roles: (1) to identify the user's state (i.e., is he/she a registered and authorized user), then (2) to detect the level of depression and provide a personalized service to relieve the depression according to the user's previous diary, such as her/his medical case and personal choice for treatments.

A. EEG and user identification

User identification is the initial stage in our pervasive EEG depression prevention system. EEG measures the electrical signals generated by the brain and recorded in the scalp of individuals. In fact, EEG has several advantages for user identification [3, 4, 5]: (1) an EEG signal is universal because every living human generates EEG spontaneously; (2) an EEG is autonomous, i.e., it cannot be forged or mimicked; at least there are no documented reports where attacks on the EEG biometric system have been fraudulently obtained; and (3) current methods enable non-invasive and safe measurement of EEG signals using patch electrodes placed on the scalp rather than by an intracranial probe.

In addition, a number of scientists have proposed a number of methods to implement EEG based individual identification, such as M. Poulos [3], R. Palaniappan [6] and A. Riera [7]. The reported results [3][6][7] demonstrate the potential effectiveness and feasibility of EEG based user identification as proposed in our system. R. Palaniappan proposed visual evoked potentials (VEP) method in [6] which records 64-channel EEG signals while the subject is stimulating by a single picture; classification is then achieved using a neural network (NN) incorporating back propagation (BP). The overall average classification performance is 99.06%, this validates the feasibility of the EEG approach to user identification. A. Riera presented an EEG based authentication biometric system through Fisher's discriminant analysis after EEG signal modeling in [7]. And the accuracy of 51 subjects can reach 96.6%. In brief, EEG can be applied to discriminate users and thus determine whether the user is authorized and who he/she is.

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B. EEG and depression

EEG can be used as an indicator of depression. It has been reported that alpha waves are associate with people's relaxation, high alpha activity is shown to be an indication of low brain activity, and vice versa [8]. Beta waves are connected to an alert state of mind. When mentioning cortical inactivation in the EEG, an increase in alpha activity is observed with a decrease in beta waves [9]. That is to say, the Beta/Alpha ratio can reflect people's mood, and then recognize depression. A low ratio scale means negative emotion while a high ratio refers to an active state. The Beta/Alpha ratio could therefore be an interesting indicator of the state of arousal in the subject [8].

The hemispheric specialization of emotion is a major aspect of neurophysiologic research into emotion [10, 11]. The left hemisphere is more involved in the processing of positive emotions and active behavior, whereas the right hemisphere is more involved in the processing of negative emotions and withdrawal behavior. The frontal cortex is particularly critical in emotional processing [12, 13]. Henriques observed that: depressed subjects had less left-sided activation (i.e., more alpha activity) than did normal control subjects. The pattern of excessive left-sided frontal alpha activation provides an effective basis for the detection of depression [14,15]. Studies have shown that dorsolateral prefrontal cortex (DLPFC) is the principal emotion processing field. Numerous studies have stated - that depression is negatively related to more laterally activity in right DLPFC and pleasant emotion is positive related to more literalism activity in left DLPFC [16].

A person who is in positive emotional state has more obvious alpha waves in his right DLPFC than left; while a person, who is in negative emotional state has more obvious alpha waves in his left DLPFC than right. The F3 and F4 electrode sites (according to International 10-20 system) are the most used positions for investigating and measuring alpha activity. This is due to their being located above the dorsolateral prefrontal cortex (DLPFC) [9]. Thus we can analyze alpha asymmetry from the F3-F4 electrodes and derive a user's emotional state.

II. METHODOLOGY

Figure 1 graphically models the methodology of our pervasive user-centered depression prevention system. The components of our system involve EEG collection, de-noise, EEG modeling, and two application interfaces: (1) user identification, and (2) depression prevention. User identification is the initial phase for our depression prevention interface. Providing that the user has passed the user identification interface test and the system has determined who he/she is, the depression prevention interface functions and provides personalized feedback to the user to enable depression relief.

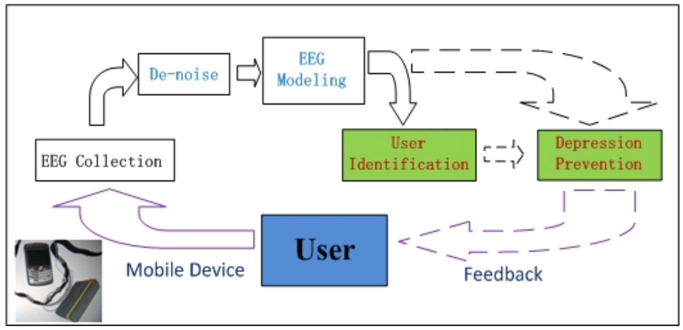

Figure 1. The methodology of EEG approach for depression prevention

A. EEG collection

Figure 2 illustrates electrode sites and the EEG recording channels. Five electrodes are used: F4 (according to International 10-20 System [17]) in reference to F3 as dipole recording and Cz in reference to left mastoid (M1) as monopole recording. The ground electrode is placed in right mastoid (M2).

To be recognized, only the EEG signal one in figure 2 is used for user identification, while both EEG signal one and EEG signal two are used to measure depression level.

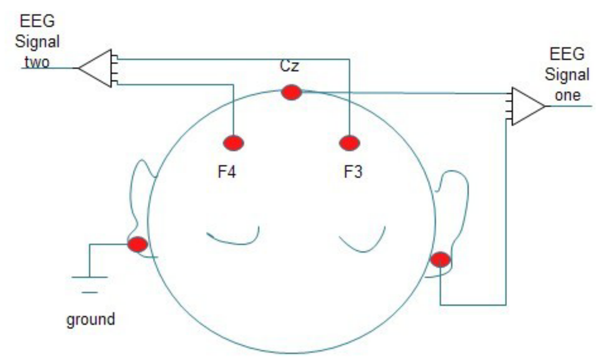

Figure 2. The measurement points of the EEG

B. EEG de-noising

To meet the pervasive and rapid requirements, discrete wavelet transform [18, 19] is selected to pre-process the EEG signals. The detailed steps of pre-processing are as follows:

1) Detection of ocular artifacts by discrete wavelet transform and high-order Haar wavelets;

2) Applying Stationary Wavelet Transform (SWT) with DB 7 (level 7) as the basis function in ocular artifacts zones identified by step 1;

3) Selecting an appropriate threshold at each level of decomposition for each identified ocular artifacts zone based on literature [20];

4) Obtaining de-noised EEG signals by inverse stationary wavelet transform (ISWT).

Compared with other de-nosing methods, such as independent components analysis (ICA), wavelet transform is an appropriate and more effective - approach for de-noising EEG signals in a small number [e.g., 5] of channels.

C. EEG modeling

In EEG modeling, EEG recordings are segmented into 4-s epochs within 2-s overlap, this enables effective EEG features of each epoch are extracted. To be recognized, the features in a user identification scenario and in a depression prevention scenario are different and are selected according to the specific applications.

To achieve high levels of effectiveness and efficiency, the Beta/Alpha ratio of the EEG signal one (shown in Figure 2) and the alpha asymmetry of EEG signal two are selected to measure the depression level in the depression prevention interface; these options are made based on the reliability demonstrated in previous research and the low computational complexity of these two features. In addition, we have selected 27 features for user identification which involve: (1) three statistical parameters on amplitudes (mean absolute amplitude, mean square and variance), (2) three Hjorth parameters [21] (activity, mobility and complexity), and (3) three principle parameters in the power spectrum (the max power density, the peak power frequency and the power density integral) respective of theta (4-7Hz), alpha (8-13Hz) and beta (14-30Hz) rhythms. The selection is based on our previous research [13], which indicated features in time and frequency domain are relatively more effective than nonlinear dynamic features for user identification.

III. EVALUATION OF EEG BASED USER IDENTIFICATION

After EEG modeling, 27 features have been obtained to recognize users. A variety of classifiers can be utilized for user identification including the k Nearest-Neighbor classifier (kNN) [22], the Fisher classifier, and the back-propagation (BP) neural network. In our system, the kNN classifier has been selected. Notwithstanding the real-time requirement, there is another reason for choosing kNN classifier. We undertook a preliminary investigation to compare the accuracy and efficiency of the BP neural network, the kNN classifier and the Fisher classifier in an EEG based cognitive interface with 12 subjects. The average true recognition rate and execution time of these three classifiers are respectively (91.6%, 0.16s), (95.83%, 0.58s) and (95.83%, 8.96s). The kNN classifier, therefore, has a relative higher recognition accuracy combined with a lower execution time when undertaking user identification in our system.

In order to evaluate the user identification performance using the features and classifier discussed in preceding sections, we have conducted two types of test: (1) client tests where a client is an individual who is authorized by the system, and (2) intruder tests where an intruder is an individual who is not authorized and whose EEG signals have not been stored in the database. The 11 subjects (6 male and 5 females) belonging to the first group were considered as clients while the 11 subjects group (6 male and 5 females) belonging to the second group were treated as intruders; the subjects all belong a 20 to 24 demographic range. EEG signals were recorded from the top of the head reference to the right lobe when the subjects sat on comfortable chair without any movement in a relaxed state with their eyes closed.

The accuracy is measured by true acceptance rate (TAR) of clients and the true rejection rate (TRR) of intruders:

- TAR of clients: the total number of correct claimed client tests or the total number of client test
- TRR of intruders: the total number of right rejection intruder tests or the total number of intruder tests

The signal-to-noise (SNR) threshold [15] is employed to correctly validate an EEG strip as a client in a template or alternatively to reject it [the EEG strip] as an intruder. Based on [7], signal-to-noise(SNR) of the probability density function (PDF) is defined as

$$SNR_i = \frac{p_i^2}{\sum_{j \neq i}^{N} p_j^2}$$

where p_i is the probability that the EEG strip comes from, and N is the number of subjects in training templates. Therefore, if the SNRi is higher than SNR threshold, the testing data is judged from subject **i**, or it will be rejected as an intruder. Obviously, an optimal SNR threshold results in a high TDR of clients and high TRR of intruders.

Figure 3 illustrates the changes of TAR of clients (the blue curve) and TRR of intruders (the red curve) with SNR threshold. Obviously, an optimal user identification technology provides both high TAR and TRR. In our test, the top TAR can reach 100% and top TRR is over 80%. However, the TAR and TRR are negatively correlated. So the choice of threshold value is up to the practical demands of specific applications. For example, where the aim is the arrest of a felon, the SNR threshold should optimally choose a SNR lower than 1 to keep TAR of client 100%, thus to avoid missing any possible candidate.

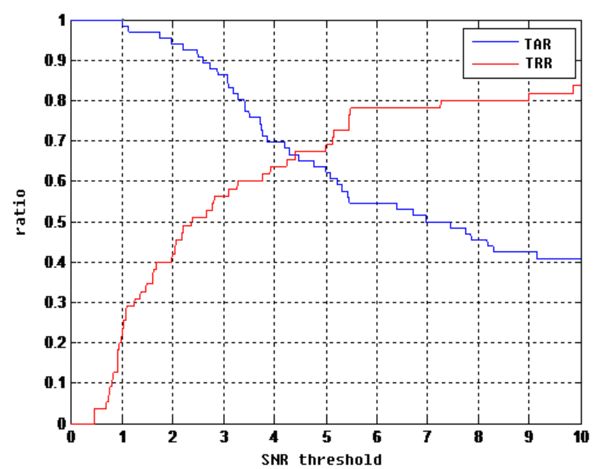

Figure 3. The true acceptance ratio and true reject ratio over SNR threshold: The x axis is each value of the SNR threshold. The blue curve refers to the trend of TAR with SNR threshold, while the red curve refers to the trend of TRR with SNR threshold.

Furthermore, an evaluation in the time dimension is also conducted in our research. This involved 11 subjects, and the results were measured by TAR. We have compared the TAR between a one-week span and a half-year span. If the TAR of clients is equivalent over the time, this EEG interface in user identification is stable and robust in the time domain. Tests were conducted a day, a week and half year after the database was built. In this test, the TAR can reach 94.60% in one-day span, 83.64% in one-week span and 78.20% half year later. Although the reduction of TAR with the time indeed occurs as EEG varies with time, the reduction of performance is, to some extent, acceptable. So, our method for user identification may be relatively stable in the time dimension.

IV. EVALUATION OF EEG BASED DEPRESSION PREVENTION

The depression prevention interface involves two steps: depression detection and depression treatment. In this paper, we mainly evaluate the effectiveness of depression as measured using EEG. If it is proved to be reliable, EEG can be an indicator of depression, and thus determine whether the user needs depression treatment and the effects of depression treatment.

Studies have identified that rational thinking and decision making systems fail to function due to lowered brain activity, especially the frontal lobe activity which governs the emotion processing and decision making functions [8, 23]. So, in the depression detection process, the signals collected from Cz are used to inspect the brain activity activation, which is implied by the Beta/Alpha power ratio. When the ratio is high, it means the brain is lively. When the ratio is low, the brain is inactive. The signals recorded from the F4 site are used to measure the valence of emotion: positive or negative [16].The EEG signals recorded from F4 in reference to F3 are equal to the right DLPFC'S EEG subtracted from the left DLPFC'S EEG. We extract the alpha difference from them and when the scale is high the brain is more positive and when the scale is low the brain is more negative [12,16].

To validate the feasibility of our system and the effectiveness of algorithms we have design the following experiment. Usually, it is difficult to identify suitable subjects suffering from depression or other negative emotional situations in a realistic time scale. Thus, in the test it is necessary to evoke the emotional response in subjects using images, sounds, or a combination of the two [1,12]. To avoid eye movements and to minimize [eye] blinking, we selected auditory stimuli. The emotion-annotated sounds (IADS), which are very useful in emotion researches [24], are available for non-profit research. 4 healthy volunteers have participated in this experiment; 2 females and 2 males aged between 20 and 24 were used in the experiment. To easily measure the efficacy of the music therapy, every subject undertook two sessions in two [different] days. In one session, after a negative stimilus, they received music treatment; this is termed a music session. In the second session, after a negative stimilus, the subjects only adjust themselves by remaining calm; we term this a static session. In the two sessions there are two stages of EEG recording: (1) in the case of a negative stimilus, we term the EEG recording Signal1, (2) in the adjustment case, we term the EEG recording Signal2.

We filter the EEG signals which are recorded from Cz and then extract the beta (14-30 Hz) and alpha (8-13Hz) band. Then Beta/Alpha ratios are computed using averages for each session. Alpha difference is extracted from EEG data recorded from F4, average alpha difference power is computed. Amount to 4 subjects' 8 sessions, every session has 2 signal ranges, we compute the average value of features' power, then use Signal2's average value to minus Signal1's average value, and get a relative value to reflect the change from Signal1 time range to Signal2 time range, we name it Change Scale. In the Static session, the Change Scale may reflect the effect of adjustment by himself/herself, after the negative stimulus during Signal1 time range. In the Music session, the Change Scale may reflect the effect of adjustment by music therapy, after the negative stimulus during Signal1 time range.

$$\text{Change Scale} = \text{Signal2} - \text{Signal1}$$

TABLE I. THE CHANGE SCALE OF THE FEATURE BETA/ALPHA POWER RATIO

	SubjecA	SubjeB	SubjecC	SubjecD
Music Session	0.0039	0.3015	-0.2679	-0.2235
Static Session	-0.1206	-0.2236	-0.0384	-0.6105

TABLE II. THE CHANGE SCALE OF THE FEATURE ALPHA'S DIFFERENCE

	SubjecA	SubjeB	SubjecC	SubjecD
Music Session	4.5738	0.1307	6.1765	2.9756
Static Session	-0.8301	-13.753	-2.743	-3.9545

From the two tables, table1 and table2, we can see that the Change Scales of the features Beta/Alpha and alpha's difference which are less than zero in some static sessions, and are greater than zero in some music sessions. For the same subject, if his/her scales of music and static sessions are above the zero (see subject B's feature alpha difference), the static session's scale must be lower than the music session, if his/her scale of music and static sessions is below the zero (see subject D's feature Beta/Alpha), the static session's scale must be lower than the music session. In these experiments, the Beta/Alpha features of subject C's fail to meet our expectation and we will carry out further investigations in our future work. We compared these experimental results to the questionnaires and correlated the emotional changes during the experiments. They are basically consistent.

Because of individual differences in EEG, we have focused on an individual's EEG features with respect to different emotions. The results suggest that when the difference scale between the right and left alpha power is lower, people are more likely to be in negative emotional state and when it is higher, people are more likely to be positive [emotional state]. When the Beta/Alpha ratio scale is lower, people may be in the negative emotional state and when it is higher, it seems that they tend to be more positive. It also suggests that music therapy plays a remarkable role in adjusting subjects' emotions. It is reasonable to apply Beta/Alpha power ratio and the alpha difference power to measure people's emotion changes on our mobile platform.

V. PERVASIVE IMPLEMENTATION OF OUR SYSTEM

There are many qualities to measure the pervasive capabilities of a system including: accessibility, ease to use, robust and mobile, etc. Our system can fit almost all of these requirements in maximum: (1) mobile and user-friendly device: examples of the device in our system is wearable and non-invasive, limited electrodes(5 electrodes in our system), and transitory EEG recording devices which is easy to operate, (2) automation: this addresses automatic data processing and transmission with and between each component of our system, (3) real-time and online interactions: these functions relate to the requirements for timely and 'real-time' monitoring and feedback in pervasive environments; all algorithms and components must be effective, efficient and implement 'real-time' online processing.

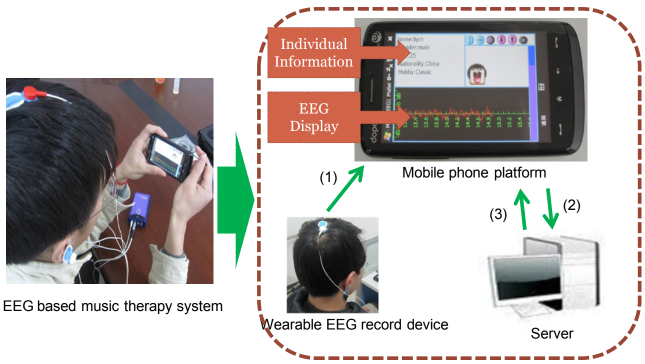

Figure 4. EEG based music therapy system: The left figure is panoramic view of the EEG based music therapy system; while the right figure is the three modules in this system.

Furthermore, using selected music as a feedback to relieve a user' depressive mood, we have integrated all the components into an EEG based mobile music therapy system funded by FP7 project. The objective of music therapy to relieve user's depression 'anytime' and 'anywhere' by listening to a user's favorite music as long as the user needs it. Additionally, the system simultaneously assesses effects of music therapy and changes the music automatically by EEG feedback (as show in Fig.4).

In the music therapy system, EEG signals are collected by wearable EEG record device and transmit to mobile phone at step (1) by Bluetooth. Then mobile phone real-timely displays EEG signals and simultaneously transmits EEG data to a server at step (2) using the WWW. The initial function of the EEG data is identification [of a specific individual], the EEG features after de-noising have to match with corresponding templates in the database stored in a server to find out his/her identity. If successful, the sever will send back the user's personal information, e.g., name and gender etc. also a feedback of a user's favorite music library based on the user's context during previous treatment is retrieved. The music library allows a user to update the music library manually; the totality of the context information will be sent back and stored in server. The second usage of EEG is to automatically change to the music selection in as dictated by the results obtained from the analysis result of the real time EEG signals; this means that if the results are not improving or are becoming worse the server may update the music library and renew the playlist in the mobile phone based on the user's contextual information.

VI. CHALLENGES AND FURTHER WORKS

While there have been a number of documented research projects addressing depression, especially in pharmacology and psychology; relatively few investigations have tried to integrate depression into a depression prevention system. In this paper, we propose an EEG approach to relieve users' depression in 'real-time' and implement it in a music therapy system.

In order to meet the needs of user-centered and pervasive applications, flexibility and the automatic combination of each component in this system is considered to be a systemic requirement. However, realizing this aim represents a significant challenge to all researchers in this field, the depression prevention system should have extensibility to support multi-modal data fusion such as electromyography (EMG), electrocardiography (ECG) and electrooculography (EOG) because pioneer research has revealed evidence that ECG has, for instance, links with mental states. Another obstacle in EEG approach is the requirements in user-friendly device, simple operation and pervasive accessibility.

Moreover, in considering user-centered design of a depression prevention system, user identification and personalized therapy is essential. Challenges not only relate to efficiency and 'real-time' requirements in user identification, but also require the robustness when a user is moving or is in an excited state. In the depression prevention interface, objectiveness is a principle issue to be addressed in achieving depression measurement and effectiveness in depression treatment.

Future work will focus on improving the efficacy of the user identification interface and depression prevention interface along with automatically personalizing the selection of treatments for depression. We believe that innovations in the near future will enable the realization of these ingenious emerging technologies and bring them to prominence and general use.

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