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IMPROVE AFFECTIVE LEARNING WITH EEG APPROACH

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Abstract. With the development of computer science, cognitive science and psychology, a new paradigm, affective learning, has emerged into e-learning domain. Although scientists and researchers have achieved fruitful outcomes in exploring the ways of detecting and understanding learners affect, e.g. eyes motion, facial expression etc., it sounds still necessary to deepen the recognition of learners affect in learning procedure with innovative methodologies. Our research focused on using bio-signals based methodology to explore learner's affect and the study was primarily made on Electroencephalography (EEG). After the EEG signals were collected from EEG equipment, we tidied the EEG data with signal processing algorithms and then extracted some features. We applied k-Nearest-Neighbor classifier and Naive Bayes classifier to these features to find out a combination, which may mostly contribute to reflect learners' affect, for example, Attention. In the classification algorithm, we presented a different way of using the Self-Assessment Manikin (SAM) model to classify and analyze learners attention, although the SAM was normally used for classifying emotions, for example, happiness etc. For the purpose of evaluating our findings, we also developed an affective learning prototype based on university e-learning web site. A real time EEG feedback window and an attention report were integrated into the system. The result of the experiment was encouraging and further discussion was also included in this paper.

Keywords: Affective learning, SAM model, EEG, classification algorithm

Mathematics Subject Classification 2000: 68Q32, 68T99

1 INTRODUCTION

In recent years, there has been an increased interest in studying affect during real-world experiences. People's moods heavily influence their ways of communicating and acting, as well as productivity [1], and also play a crucial role in learning process. However, detecting students' emotion and attitude without interfering is usually a complex task, so practices are often difficult to carry out, especially in distance education program.

EEG signal is a measurement of currents that flow during synaptic excitations of the dendrites of many pyramidal neurons in the cerebral cortex [2]. They can be captured by multiple-electrode EEG machines either from inside the brain, over the cortex under the skull, or certain locations over the scalp, and can be recorded in different formats. The signals are normally presented in the time domain.

As the electrophysiology implication of neural activities, EEG is proved to have close relationships with affect during learning process. However, although it has been researched over decades, the application of EEG in the field of affective learning has not been fully developed.

In this paper, we proposed a solution of applying EEG signal processing and classification algorithms in the application affective learning via series of experiments. We also developed an affective learning system based on our findings to validate its applicability.

We will briefly introduce concepts and relevant research works presented in this paper, including affective learning, the SAM model, classification algorithms in Section 1. Then we will present quantitative research on EEG to reflect the level of attention in Section 2, as well as prototyping, noise removement and classifiers applied. In Section 3, experiment process and analysis are presented while conclusions and discussion are proposed in Section 4.

1.1 Affective Learning

Affective learning represents an internalization of positive attitudes toward course content, subject matter or the instructor [3]. Affective reactions include feelings of self-confidence, self-efficacy, attitudes, preferences, and dispositions which may be viewed as a specific type of learning outcome [4], and affective learning activities are directed at coping with these feelings that arise during learning, and that positively or negatively impact the learning process [5].

Dirkx [6] suggests that the role of emotions is much more than a motivational concern, and that the active dimension provides the foundation on which rest the practical, conceptual and imaginative modes of learning. On the one hand, emotional experiences lend us the ability to better comprehend and regulate our activities, to understand our motivations, and how to fulfil our needs [7]; on the other hand, the role of emotion in stimulating thought should be taken into consideration.

1.2 The Self-Assessment Manikin (SAM)

The SAM model [8] (Figure 1) is a standardized system to assess emotions on the valence and arousal dimensions (and dominance, if wanted). Emotions are then mapped into points in the two/three-dimensional planes accordingly. In practice, in order to determine their emotional status, users will be asked to rate their emotions on the SAM model by selecting certain class on each dimension.

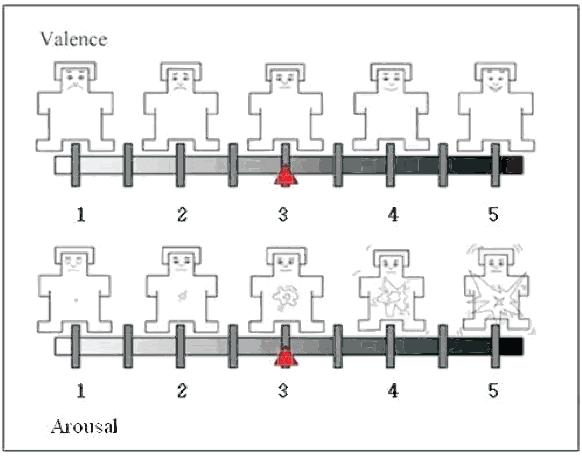

Fig. 1. Self-Assessment Manikin

1.3 Classification Algorithms for Analyzing EEG Data

Because of the complexity of EEG signals, we proposed our solution of applying classification algorithm to EEG processing, with the aim of finding the correlation between EEG and affect. Before the classifier can be used, it must be trained by training data. Users' rank on the SAM was determined according to 13 EEG feature values.

We have implemented two different classifiers, k-Nearest-Neighbor classifier [9] and naive Bayes classifier [10].

Nearest-neighbor classifiers learn by analogy. The similarity between the test and sample is indicated by the distances between the given test tuples and training tuples. Tuples are characterized by their attribute values. Each tuple with n attributes can be mapped into a point in an n-dimensional space. Given a certain tuple, a k-nearest-neighbor classifier searches the pattern space for k training tuples which are closest to the input tuple. They are the k "nearest neighbors" of the one.

"Closest" is defined in terms of a distance metric, such as Euclidean distance. The Euclidean distance between two points or tuples, say, $X_1 = x_{11}, x_{12}, \ldots, x_{1n}$ and $X_2 = x_{21}, x_{22}, \ldots, x_{2n}$, is

$$dist(X_1, X_2) = \sqrt{\sum_{i=1}^{n} (x_{1i} - x_{2i})^2}.$$

For k-nearest-neighbor classification, the unknown tuple is assigned to the most common class among its k nearest neighbors.

Naive Bayes are simple Bayes networks which are composed of DAGs with only one root node called parent, which implies the unobserved node, as well as serval children corresponding to observed nodes. It has the strong assumption that the child nodes, in context of their parent, are independent. Naive Bayes classifier is widely used for classification due to its efficiency and accuracy.

After removing noise, for each subset of features, EEG data is classified into five classes along valence and arousal dimension.

To determine the group of features to be selected, we ran the algorithms several times, with different groups of features. Compared with the Self-Assessment Manikin, we can calculate the correct classification rates which are used to assess its performance and to determine whether these features shall be selected.

1.4 Relevant Research

Considerable prior research is engaged in recognizing emotions with computers, e.g. recognizing emotion from speech, facial expressions or a fusion of both methods. Measuring emotion from brain activity is a relatively new method, although some valuable conclusions have been published.

Bo Hong et al. [11] from Tsinghua University suggest that ApEn generally tends to increase during the process people pay attention to some stuff. In the work of Delft university [1], participant's EEG signals was recorded and processed when they were viewing pictures selected from International Affective Picture System (IAPS) database. Their results show that EEG data contains enough information to recognize emotion.

As we can see, most of these studies based on EEG signals processing aimed at recognizing common emotions. Moreover, most existing studies obtain affective information through speech, motion, gesture, facial expression, etc. Designing affective learning experiments on learners while introducing limited disturbances on learners is one of the challenges. New features need to be introduced to enrich the ways of understanding learners'affect better, such as EEG.

On the one hand, we concern more about whether or not the learner focuses on the learning materials, and whether the learning materials can stimulate the learner's active thinking rather than normal emotions like sad, angry and so on. On the other hand, we can see that Positive-Negative and Attention-Inattention assessment may be correlated, as well as Calm-Exciting and Active Thinking-Thinking Suspending. During learning process, calmness in a sense is connected with thinking suspending, and excitement, in some ways, means active thinking.

So we modify the SAM model. The two dimensions measuring are defined as valence (Attention-Inattention) and arousal (Active Thinking-Thinking Suspending). Each dimension is divided into 5 classes.

2 QUANTITATIVE RESEARCH ON EEG TO REFLECT THE LEVEL OF ATTENTION

There are a lot of features of EEG signals which need to be taken into consideration, actually may be more than needed. Which group of features should be used is a big problem which needs to be solved.

Our prior work [12, 13] did some analysis on EEG signals on both time and frequency domains, which proved that EEG had a close relation with emotions in learning state.

However, the result is still limited, so we choose to use data mining to find the information hidden in the EEG data. Figure 2 shows the procedure of our experiments. There are basically 3 steps:

1. Removing noise.
2. Feature extraction.
3. Processing with classification algorithms.

Basically, we used FastICA [14] and ApEn [15] algorithms for noise removal and feature extraction. ApEn is a statistical property of EEG signal which can be used to quantify the complexity or irregularity of a signal as well as to describe the rate of producing new information. A robust estimate of ApEn can be gotten by using short, noise data sets. For the EEG data, it is a positive value. Larger ApEn values imply more complexity or irregularity in the data.

FastICA is embraced by many researchers in blind source separation (BSS) of linear mixtures. It is an algorithm for ICA, which aims at recovering independent sources from mixed signal without knowing the mixed matrix and specific knowledge of the sources under weak assumption that the sources are linearly mixed. As one of the Independent Component Analysis (ICA) methods, FastICA is a multivariate

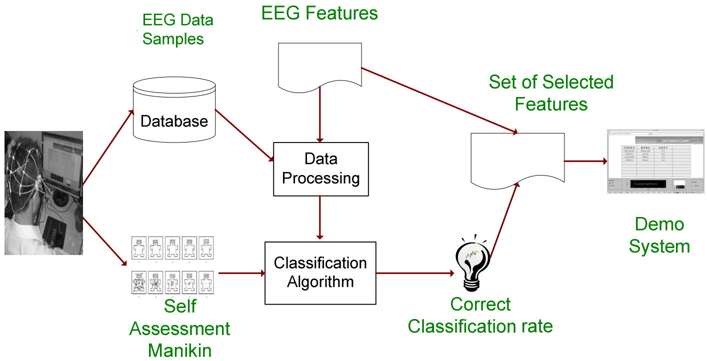

Fig. 2. Procedures of the experiments

approach for denoising or separating elelctroencephalogram (EEG) signals that have become increasingly popular in recent years.

In the following sections, we will describe these 3 steps in details.

2.1 Removing Noise

Sources of noise in EEG may be static electricity or electromagnetic fields produced by surrounding devices. In addition to this external noise, the EEG signal tends to be heavily influenced by artifacts that originate from body movement or eye blinks [1]. Thus, noise must be removed from EEG data before data processing.

The relevant information in EEG, at least for emotion recognition, is found in the frequencies below 30 Hz. Therefore, all noise with higher frequencies can be removed using a low pass filter. In our program, we use FastICA combined with matched filters to realize denoising.

2.2 Feature Extraction

There are 13 EEG features used in our work, shown below.

1. Eeg_fir_mean: Mean amplitude of EEG raw data filtered by a 2–40 Hz FIR filter.
2. Alpha_mean: Mean amplitude of alpha wave.
3. Alpha_pp_mean: Peak to peak amplitude of alpha wave.
4. Alpha_power_mean: Mean power of alpha wave.
5. Alpha_Pmax: Max power of alpha wave.
6. Alpha_H: Mean approximate entropy of alpha wave.
7. Alpha_F0: Center frequency of alpha wave.
8. Theta_mean: Mean value of theta wave.
9. Theta_pp_mean: Peak to peak amplitude of theta wave.

10. Theta_power_mean: Mean power of theta wave.
11. Theta_Pmax: Max power of theta wave.
12. Theta_H: Mean approximate entropy of theta wave.
13. Theta_F0: Center frequency of theta wave.

The values of these features can be calculated by FastICA, and ApEn. For example, the value of Alpha_mean can be obtained by FastICA, and that of Alpha_H by ApEn. The values were organized in a table which would be processed by the classification algorithms later.

2.3 Processing with Classification Algorithms

As mentioned above, we implemented two classifiers, k-Nearest-Neighbor Classifier and Naive Bayes Classifier. The correct classification rate is calculated depending on users' rating on the Self-Assessment Manikin model.

The interface of our software is shown in Figure 3.

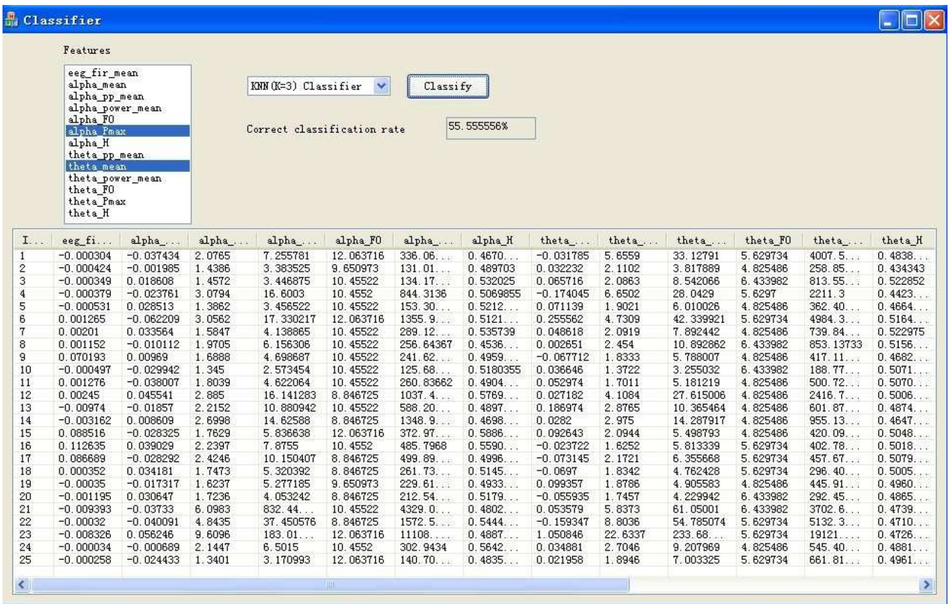

Fig. 3. The main interface of program

After these 3 steps, a group of features with the highest correct classification rate will be discovered. With the selected group of features along valence dimension, we developed an affective learning system (Figure 4). The interface includes components of web browser, user information, and feedback of affective state information. When the learner is browsing web pages, his/her EEG signals are recorded and processed. If the learner is concentrated, the feedback may urge the learner to adjust his/her affect and pay attention to the learning content, or the web server can change a different strategy such as changing learning content accordingly.

Fig. 4. Affective learning system

3 EXPERIMENTAL RESULT AND ANALYSIS

We have conducted an experiment on the web site mentioned above, with 10 participants, including two teachers and eight students. Each time, the participants spent 20 minutes on the web site to study different learning materials and their EEG signals have been recorded. We used Nexus to collect EEG signals, and raw data was extracted. The output rate was 256 samples/sec.

Meanwhile, the participants are asked to rate their affect along both dimensions on the Self-Assessment Manikin which is taken as the correct class the EEG signals belong to.

After removing noise from EEG signal, 25 samples are selected for processing. First, algorithms of FastICA and ApEn are used for feature extraction. Second, we apply k-Nearest-Neighbor classifier and Naive Bayes classifier to the EEG data.

We divide the 25 samples into three sets, for a certain feature group we run every algorithm three times, each time a different set is used for testing and the other two for training the classifier. We take the average correction rate (number in brackets) as a rational evaluation of correct classification rate.

3.1 Experimental Result

Part of the experimental result is shown in Table 1 and Table 2. In these tables, the features in brackets denote that the presence or absence of them seems to have no influence on the classification results and the numbers in brackets denote the average of the three numbers in front of it.

	Naive Bayes	KNN($K=1$)	KNN($K=3$)	KNN($K=5$)
alpha_power_mean alpha_Pmax theta_mean theta_H	66.7 %, 22.2 %, 22.2 % (37.0 %)	33.3 %, 11.1 % 44.4 % (30.0 %)	44.4 %, 22.2 % 33.3 % (33.3 %)	44.4 %, 44.4 % 33.3 % (40.8 %)
alpha_power_mean alpha_Pmax theta_F0 theta_H (theta_mean)	44.4 %, 22.2 %, 22.2 % (30.0 %)	55.6 %, 11.1 %, 44.4 % (37.0 %)	44.4 %, 11.1 %, 33.3 % (30.0 %)	44.4 %, 44.4 %, 33.3 % (40.8 %)
alpha_F0 theta_H alpha_power_mean alpha_Pmax (alpha_H)	55.6 %, 22.2 % 33.3 % (37.0 %)	44.4 %, 33.3 %, 33.3 % (37.0 %)	66.7 %, 44.4 %, 44.4 % (51.9 %)	55.5 %, 44.4 %, 44.4 % (48.1 %)
alpha_H theta_H	55.6 %, 33.3 %, 33.3 % (40.8 %)	11.1 %, 22.2 %, 11.1 % (15.6 %)	33.3 %, 44.4 %, 33.3 % (37.0 %)	55.6 %, 44.4 %, 44.4 % (48.1 %)

Table 1. Part of the result of correct classification rate for 4 feature groups in the valence (Attention-Inattention) dimension

	Naive Bayes	KNN($K=1$)	KNN($K=3$)	KNN($K=5$)
eeg_fir_mean alpha_mean alpha_F0 alpha_H theta_power_mean	66.7 %, 22.2 %, 00.0 % (29.6 %)	11.1 %, 00.0 %, 11.1 % (7.5 %)	33.3 %, 33.3 %, 33.3 % (33.3 %)	11.1 %, 22.2 %, 22.2 % (18.5 %)
theta_power_mean	44.4 %, 22.2 %, 11.1 % (25.9 %)	44.4 %, 33.3 %, 55.6 % (44.4 %)	11.1 %, 22.2 %, 22.2 % (18.5 %)	22.2 %, 11.1 %, 11.1 % (14.8 %)
eeg_fir_mean alpha_mean alpha_H theta_power_mean	33.3 %, 22.2 %, 00.0 % (18.5 %)	33.3 %, 00.0 %, 33.3 % (22.2 %)	55.5 %, 22.2 %, 33.3 % (37.0 %)	22.2 %, 11.1 %, 22.2 % (18.5 %)
alpha_mean alpha_Pmax theta_F0	33.3 %, 22.2 %, 11.1 % (22.2 %)	11.1 %, 11.1 %, 33.3 % (18.5 %)	44.4 %, 22.2 %, 33.3 % (33.3 %)	44.4 %, 33.3 %, 33.3 % (37.0 %)
theta_F0 theta_Pmax theta_H	33.3 %, 22.2 %, 55.6 % (37.0 %)	11.1 %, 00.0 %, 22.2 % (11.1 %)	22.2 %, 22.2 %, 22.2 % (22.2 %)	22.2 %, 22.2 %, 22.2 % (22.2 %)
theta_power_mean theta_Pmax	33.3 %, 22.2 %, 33.3 % (29.6 %)	22.2 %, 11.1 %, 66.7 % (33.3 %)	22.2 %, 44.4 %, 44.4 % (37.0 %)	33.3 %, 22.2 %, 22.2 % (25.9 %)
alpha_power_mean alpha_F0 theta_H alpha_Pmax	33.3 %, 33.3 %, 44.4 % (37.0 %)	00.0 %, 22.2 %, 33.3 % (18.5 %)	22.2 %, 33.3 %, 44.4 % (33.3 %)	22.2 %, 22.2 %, 33.3 % (25.9 %)

Table 2. Part of the result of correct classification rate for 6 feature groups in the arousal (Active thinking – Thinking stagnation) dimension

3.2 Analysis

Our result shows that in valence dimension, performance of the group of 4 features – alpha F0, theta H, alpha power mean and alpha Pmax – is the best.

We can see the classification rates in valence dimension are higher than in arousal dimension. We think it suggests that the EEG signals contain more information to recognize the emotion in valence (Attention-Inattention) dimension than in arousal (Active Thinking-Thinking Suspending) dimension, or features that can reflect affect in the arousal dimension are not included in our experiment.

Based on the experimental result above, we obtained some other analysis results.

3.2.1 The Best Classifier for Each Dimension

As we can see, even if applied on the same feature group, sometimes the variance between the performance of two classifiers is significant.

In valence dimension, the best classifier is KNN($K = 5$). The results of average correct classification rates are 40.8 %, 40.8 %, 48.1 % and 48.1 %. The worst classifier is KNN($K = 1$) with the results of 30.0 %, 37.0 %, 37.0 % and 15.6 %.

In arousal dimension, the best classifier is the KNN($K = 3$) classifier, and the worst is KNN($K = 1$) classifier.

It can also be noted that in the unit like 00.0 %, 22.2 %, 33.3 % (18.5 %), the difference among the first three numbers is significant; this is because the result is heavily influenced by the training data, and we consider the feature group unavailable.

3.2.2 Analysis of Using SAM Model to Measure Affect

SAM model is used to measure emotion. However, emotion in learning state is different from normal emotions, it concerns affect in learning process, for example, attention and active thinking. So we did some modification to it. The valence and arousal dimension is changed into valence (Attention-Inattention) and arousal (Active Thinking-Thinking Suspending).

As a result, our experiment proved that the modification is practicable and effective. However, affect is so complex that it is difficult to measure and interpret accurately, only two dimensions may not be enough, further work is still needed.

3.2.3 Same Features with Different Classifiers

The results show that in valence dimension, when using KNN($K = 3$) classifier with the set of four features including alpha_F0, theta_H, alpha_power_mean and alpha_Pmax demonstrates the best performance. The correct classification rates are the highest, shown as 66.7 %, 44.4 %, and 44 %, with the average of 51.9 %.

For the same four features, the correct classification rates are 55.6 %, 22.2 %, 33.3 % with the average of 37.0 % for Bayes classifier. The difference between the two is notable, shown in Figure 5.

Meanwhile, for the 4 classifiers, the average correct classification rates are 37.0 %, 37.0 %, 51.9 % and 48.1 %, respectively. So we come to the conclusion that these feature groups contain some information that can be used to recognize affect in learning state.

In the arousal dimension, when using KNN($K = 1$) classifier, the theta_power_mean feature has the best performance with the correct rate of 44.4 %, 33.3 %, 55.6 % and average of 44.4 %. However, applying other classifiers with the same feature does not show such good results (25.9 %, 18.5 % and 14.8 %). This may indicate that the choice of features has a great impact on the result or good performance may appear occasionally.

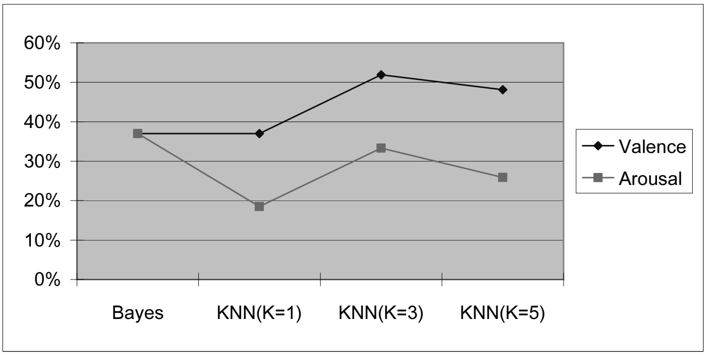

Fig. 5. Comparison of the correct classification rates of a same feature group on two dimensions

As a discussion, the feature group of alpha_F0, theta_H, alpha_power_mean and alpha_Pmax contains some information that can be used for affect recognition through EEG signal processing in the dimension of valence (Attention-Inattention). However, in arousal dimension the result is not good enough to be applied in practice.

Although the correct classification rate is not so high to be that convincing, it does provide us a new approach to assess affect in learning state. Most existing studies sense affective information through speech, motion, gesture, facial expression, etc., which are generally recorded by pressure sensor, camera and eye movement tracking techniques. We believe EEG will be a good supplement for affective learning. Using the combination of EEG with other information we may achieve a higher accuracy rate of understanding affect.

4 CONCLUSION

In this paper, we have analyzed progress and approaches applied in supplementing user information in affective learning with EEG data. We intend to find the relationship between the characteristics of the brain activity and the emotion changes in a learning process and to apply it to practice.

With the feature extraction algorithms and data mining methods, we processed EEG data and obtained a group of features that can represent affect of learners. On this basis we developed relevant hardware and software which are used to carry out real-time monitoring and interaction with learners. With the feedback, learners can make an adjustment to their emotions so as to promote the quality of study.

The outcomes of the research can also contribute to assisting in understanding of learners' emotion in learning process. The SAM model is also introduced to affective learning, which proved to be effective and convictive.

In the future, we will first use more classifiers such as support vector machine, neural networks and so on. Second, in order to enhance the correct classification rate in both dimensions, i.e., to find a better group of features that can be used to recognize affect more accurately, more features are needed, for example, AR model parameters, Hjorth parameters and bispectrum parameters. Affective learning research based on ERP will also be taken into consideration.

Moreover, with the development of manufacturing technology, EEG equipment is getting more and more portable and miniature. In the future, we could use Bluetooth or other mobile communications for data transmission and gain real-time access to user information.

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