



Analysis of Students' Learning Emotions Using EEG

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Abstract. Advances in Internet technologies have enabled students to improve their learning experiences by making use of diverse sources of information and knowledge. The teaching model of the twenty-first century is gradually changing. The learning center of the student is no longer a teacher but the student himself/herself. Today, teachers are no longer the soul of teaching but the student is increasingly involved in the learning process. But students are easily affected by emotions in learning efficiency. Research has shown that learning experience can be good when students are in positive moods whereas negative emotions have the opposite effect. To improve the student's learning efficiency, teachers who are students must understand their learning emotions. When students' emotions are negative, teachers must step in to provide assistance to the students in their studies. This study analyzed brain wave signals and classified brain wave emotions by using the support vector machine (SVM) method. Brain wave emotional analysis results provide the teacher's emotions during the learning process. When students are in negative moods, teachers can intervene to assist students during learning in due course.

Keywords: EEG · Emotional analysis · Learning emotions

1 Introduction

Emotions [1] have a great influence on life and are more directly related to learning [2–4]. Focus is the fundamental of students' learning effect, and the fundamental of mindfulness is emotion. Positive emotions can provide students with a sense of achievement and satisfaction in their studies, which in turn stimulates their desire to study more. So positive emotions help to keep concentration while learning, which in turn improves the learning efficiency [5]. However, negative emotions bring anxiety, disappointment, and frustration to students in their studies. When students are constantly in a negative mood, they begin to get confused about what they are learning and may even start to get bored with the idea being presented to them. When these feelings begin to arise, the student's focus on learning begins to decline, leading to poor learning outcomes. Today's teaching strategy is a teaching model centered on student

learning. If a teacher who is a student can understand the student's learning emotions, he/she can help the student learn better in due course. Teachers are better able to play the role of "assistant".

Brain waves [6] are physiological signals in the human body. When a person is stimulated externally, nerve cells in the brain are activated and a current is released. Brain waves are a direct reflection of the state of mind and cannot be tampered with. Based on these ideas, we believe that the emotional characteristics of brain wave data should be extracted by classification algorithms, because brain wave data, human emotional and physiological conditions are related. In recent years, many studies [7–10] have explored and classified simple emotions. To analyze brain wave emotions, we used support vector machine (SVM) algorithms [11] to classify brain wave data. Finally, we use the actual emotional analysis based on the emotional state of students to determine the most appropriate teaching strategy. The experimental results obtained show that our system can really improve the learning efficiency of students.

2 Background and Related Works

2.1 Electroencephalogram

In 1875, Richard Cotton, Professor of Physiology, discovered electrical reactions from the brain on the scalps of animals. These current sensing are called brain waves. Brain neurons produce an electrical response during exercise. Studies have shown that both physical movement and emotional response or physiological state of the body are associated with electrical reactions [12–14]. That is, brain waves reflect the body's state of every minute. So brain waves can be studied for a variety of emotions. The frequency range of brain waves is 0–200 Hz. The International Federation of Societies Electroencephalography and Clinical Neurophysiology classifies brain waves into five different types which include: α wave, β wave, γ wave, δ wave, and θ wave.

2.2 Emotion

Emotions can basically be divided into positive and negative emotions. The psychologist Ekman [15] divides human emotions into four basic types which include: fear, anger, sadness, and happiness. During infancy, humans have these four basic emotions. We describe these four emotions in Table 1.

2.3 Support Vector Machine

The support vector machine is a binary linear classifier. A hyperplane is searched in space by using formula (1). This hyperplane separates two different categories as clearly as possible in space. The motivation for supporting high dimensional data in vector machines is to make it easier to classify by using the technique of kernel functions, which increase the data interval in the feature space or separating the data that was previously entangled by make data from low dimensions to high dimensions.

$$f(x) = w^T x + b \quad (1)$$

x is the input signal, which is brain wave data in our study. Brain waves are divided into δ wave, θ wave, low α wave, high α wave, low β wave, high β wave, low γ wave and medium γ wave according to frequency. Record brain waves data $x_{EEG}(t) = \{x_\delta(t), x_\theta(t), x_{l\alpha}(t), x_{h\alpha}(t), x_{l\beta}(t), x_{h\beta}(t), x_{l\gamma}(t), x_{m\gamma}(t)\}$. W is the weight vector and b is the optimal. Use these parameters to calculate the distance between the data and the hyperplane, and find the hyperplane with the largest margin to accurately classify.

Table 1. Four basic emotions.

Emotion	Description
Fear	The instinctive behavior of a creature or person in general when at risk in his/her/its lives Fear can cause physical phenomena such as a change in heart rate, elevated blood pressure, night sweats, tremors, and even symptoms of cardiac shock
Anger	Emotions are being violated, disrespectful, or mistreated, leading to instinctive self-defense of their fighting response. Emotions are angry, micro-angry, resentful, irritable, hostile, and more extreme, for hatred and violence
Sadness	Usually psychologically frustrated and failed, feeling depressed, emotions have sadness, depression, self-pity, loneliness, despair, and morbid severe depression
Joy	Emotion sits in a state of euphoria, with joy, happiness and satisfaction, and self-satisfaction, pride and excitement in the senses

3 Problem Definition

Some studies [16, 17] have used specific brain waves to classify emotions. But each brain wave reflects a different physiological response. So we had to consider all the brain waves when performing brain wave analysis. In other words, a complete analysis of brain waves must include all waves over the same time period. In this study, we considered all eight brain waves: δ , θ , low α wave, high α wave, low β wave, high β wave, low γ wave, and medium γ wave. We believe that in order to obtain more accurate emotions, all biological features in brain waves must be considered.

First, we set up a model group (VM) and a test group (VT). Each data point in the brainwave data set of the two groups is an eight-dimensional vector. Each data point in the data collection has an emotional label, $Emo_l = \{Joy, Anger, Sadness, Fear\}$. μc is the accuracy of the classification. The main goal of this study is to find the largest μc . μc can be expressed by using formula (2):

$$\mu c = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

where TP (True Positive) refers to the number of samples that a positive class is correctly classified. TN (True Negative) refers to the number of samples that negative classes are correctly classified. FP (False Positive), also known as type-1 error, refers to

the number of samples in which negative classes are misclassified into positive classes. *FN* (False Negative), also known as type-2 error, refers to the number of samples in which positive classes are misclassified into negative classes. Thus, by maximizing *TP* and *TN*, can achieve the best μc .

4 Experimental Settings and Procedure

4.1 Experimental Settings

In this study, we chose SVM as our classification algorithm. First, we developed an emotional model of our SVM. The emotional model is built from the brainwave data of the VM. Study use NeuroSky Mind Wave Mobile Headset to collected brainwave data. We look for several 5–10 min film videos from YouTube that included different types of plots, such as comedy, tragedy or horror. We used the film as a stimulus, inviting students to watch it and we collected four types of brainwave data namely, Joy, Anger, Sadness, and Fear. We collected brainwave data of VT during student learning. Based on the established emotional model, we analyzed the brainwave data of VT by using the SVM method. Figure 1 shows how the subject wears an brain-wave instruments and collects brain waves. In Fig. 1, the subject is watching the film we prepared to stimulate the corresponding emotions, and the measured brainwaves will contain emotional data to build the emotional model.



Fig. 1. Experimental setup.

4.2 Experimental Procedure

The main purpose of this study is to help teachers provide timely assistance when students study. The study explores if students can be in a positive mood during learning and if the mood is negative, the teacher can provide help in a timely manner. The results shown in Fig. 2 demonstrate that our accuracy for emotion classified is on average higher than 80%.

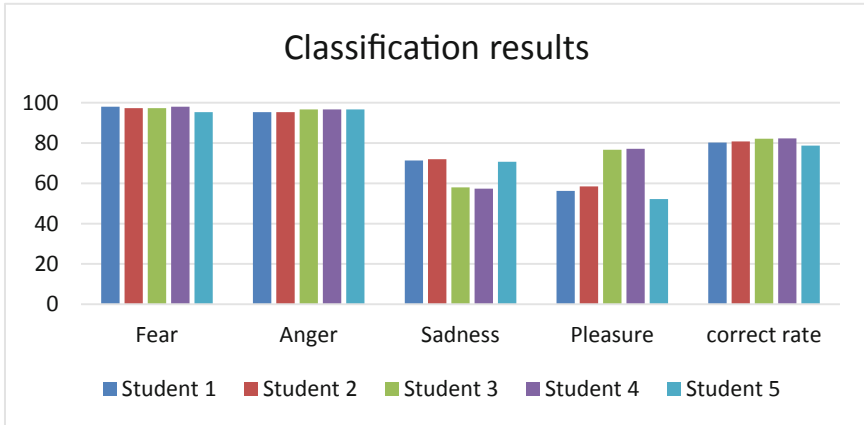


Fig. 2. Experimental results.

During the actual experiment, we asked students to wear brain-wave instruments before the class starts. We experimented with hands-on courses for the android app. Each student team must complete a project to pass this course. We selected two groups of students in the course to conduct the experiment. Each team consists of four students. One of the teams used our system in the course, and each student wore a brain-wave instrument. The other group did not. Each time for test in about 30–40 min.

The instruments work well with Bluetooth on students' phones. During the class, brain wave signals are sent to our servers for analysis. The brain wave meter transmits the brain wave signal to the phone via Bluetooth. Mobile phones send brainwave information to our system via the Internet. The student's brain wave signals are analyzed by our system. In the system, SVM classifies emotions through emotional models. Finally, the results of the analysis (as shown in Fig. 2) were returned to the students' and teacher's phone.

5 Experimental Results

During the course, the teacher is no longer a soul figure, but an auxiliary one. *How can a teacher help a student when he/she learns his/her own way?* In the experiment, our system shows each student's mood. When there is a dispute with the team, the representative needs the teacher's help. Table 2 is the advice given to the teacher, according to the emotional state of the students during the learning process, it is recommended that the teacher respond. This means that teachers will be guided by the student's learning mood, and after discussion with the students, they can provide timely intervention. In other words, if someone in the team is in trouble, the teacher will offer to help. Difficulties include disputes, sadness and so on. On the other hand, the other team does not consider the students' emotions, so teamwork is weak.

After the experiment, some key performance pointers are provided to help teachers evaluate the student's learning performance. Key performance pointers include learning

Table 2. How teachers should help students in different emotion.

Positive	Negative
When students are active, guide students to embrace more diverse ideas	When students are distracted, ask students to maintain a high degree of concentration
When students are overly concentrate, remind students to reflect on their own methods	When a student is angry or depressed, remind the student to relax and restore his/her mood

pleasure, attention, creativity and critical thinking, team communication, self-exploration, responsibility and project integrity. We also found that by using our system, we can help teams discuss activities more frequently, collaborate more, become more learned, and express themselves more actively. We also found that there are fewer exchanges among the peers if our proposed system does not find the cause of the problem. The reason is because teachers cannot easily understand the student's emotions in the curriculum. Thus, when students encounter some problems during the learning process, the teacher cannot modify the student's thinking in real-time.

6 Conclusion

In today's self-learning center, students promote self-study through the interaction between assistants and peers. But teachers often fail to act as a assistant in time. Our system helps teachers mentor students and guide them in a timely manner by learning emotions, focusing on thinking, and improving communication among peers. Our experiments show that using our system allows students to learn while being in a happy mood. At the end of the experiment, we found that by using our system, the efficiency of team learning and student learning is improved.

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