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Affective e-Learning: Using “Emotional” Data to Improve Learning in Pervasive Learning Environment

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ABSTRACT

Using emotion detection technologies from biophysical signals, this study explored how emotion evolves during learning process and how emotion feedback could be used to improve learning experiences. This article also described a cutting-edge pervasive e-Learning platform used in a Shanghai online college and proposed an affective e-Learning model, which combined learners’ emotions with the Shanghai e-Learning platform. The study was guided by Russell’s circumplex model of affect and Kort’s learning spiral model. The results about emotion recognition from physiological signals achieved a best-case accuracy (86.3%) for four types of learning emotions. And results from emotion revolution study showed that engagement and confusion were the most important and frequently occurred emotions in learning, which is consistent with the findings from AutoTutor project. No evidence from this study validated Kort’s learning spiral model. An experimental prototype of the affective e-Learning model was built to help improve students’ learning experience by customizing learning material delivery based on students’ emotional state. Experiments indicated the superiority of emotion aware over non-emotion-aware with a performance increase of 91%.

Keywords

E-Learning, Affective, Emotion detection, Pervasive computing

Introduction

In the past decade, e-Learning has evolved from Computer Aided Instruction, through Intelligent Tutoring System, to Smart Classrooms, and to Mobile Learning (e-Learning with mobile devices). Today, e-Learning becomes heavily learner-centered, emphasizing pervasive and personalized learning technologies. Also known as ubiquitous or ambient learning, pervasive learning refers to learning that is available anywhere anytime (www.pervasive-Learning.org). Pervasive learning is supported by wireless communication and wearable computing. “In combination with session and service mobility as well as device independency, the arising learning environments should have the potential to be accessed by anyone at any place and any time. Learning wherever and whenever needed is to become possible” (http://wwwra.informatik.uni-rostock.de/perel08/). E-Learning should not only generate good learning outcomes, but also better engage learners in the learning process. From engaged learning perspective, truly engaged learners are behaviorally, intellectually, and emotionally involved in their learning tasks (Bangert-Drowns & Pyke, 2001; Wang & Kang, 2006).

The influence of emotions on learning is still under-emphasized. Recently, a growing body of literature (e.g., Currin, 2003; Dirkx; Hara & Kling, 2000; Kort, Reilly & Picard, 2001; Wang & Kang, 2006) has begun to espouse the central role of emotion to any learning endeavor and outcomes, especially in online learning. Continuous and increasing exploration of the complex set of parameters surrounding online learning reveals the importance of the emotional states of learners and especially the relationship between emotions and effective learning (e.g., Kort, Reilly & Picard, 2001). Research (Isen, 2000) also demonstrates that a slight positive mood does not just make you feel a little better but also induces a different kind of thinking, characterized by a tendency towards greater creativity and flexibility in problem solving, as well as more efficiency and thoroughness in decision making. These findings underscore the important effects of emotions on learning. Human brain is not just as a purely cognitive information processing system, but as a system in which both affective functions and cognitive functions are inextricably integrated.

In this paper we describe a state of the art e-Learning platform based at Shanghai and we have augmented this with the research of affective computing coined by Picard (1997). Affective computing describes computer methods that are related to, derived from or deliberately designed to influence, emotions. It involves two areas: emotion synthesis used to artificially imitate some of the physical or behavioral expressions associated with affective states, and emotion analysis which is often employed in decision making for interactive systems. Emotion synthesis is useful to develop ways to communicate with humans at a subjective level involving social participation, for example using robots. Emotion analysis could be used to monitor the emotional state of a subject, taking actions based on the type of individual feeling being experienced. Some computing systems are capable of displaying immediate reactions to people's feelings by incorporating a combination of both emotion detection and emotion synthesis(Garzon, Ankaraju, Drumwright, & Kozma, 2002; Morishima, 2000). "We believe that existing and future affective and cognitive research needs to be adapted and applied to actual learning situations. Thus far, most research on emotions does not bridge the gap to learning"(Picard et al., 2004). This study intends to fill in this gap, by discussing how physiology-based emotion sensing is integrated into the e-Learning platform. The goal of this study is to help improve students' learning experience by customizing learning material delivery based on the learner's emotional state (e.g. curiosity, confusion, frustration, etc).

This article describes the development of an affective e-Learning model, and demonstrates the machine's ability to recognize learner emotions from physiological signals. In the following, we first introduce related work and our pervasive e-Learning platform; we then describe our "emotion-integrated" e-Learning architectural model and its theoretical foundations. Afterwards, we present the preliminary experiments, emotion classification, and data analysis. Finally, we summarize the findings and describe further research planned for the near future.

Related Work and the Pervasive e-Learning Platform

The extension of cognitive theory to explain and exploit the role of affect in learning is still in its infancy (Picard et al., 2004). Studies carried out by the AutoTutor Group presented evidence that confusion and flow were positively correlated with learning gains, while boredom is negatively correlated (Craig, Graesser, Sullins, & Gholson, 2004). Stein and Levine (1991) identified a link between a person's goals and emotions. Their model adopts a goal-directed, problem-solving approach and predicts that learning almost always occurs during an emotional episode. Research revealed that emotion can also affect learner motivations (Keller & Suzuki, 1988). Kort, Reilly and Picard (2001) proposed a four quadrant learning spiral model in which emotions change when the learner moves through the quadrants and up the spiral. They also proposed five sets of emotions that may be relevant to learning. However, empirical evidence is needed to validate the learning spiral model and to confirm the effects that these emotions might have on learning.

The Affective Computing Group at MIT's Media Lab is investigating the interplay of emotion, cognition, and learning as part of its "Learning Companion" project. This project aims to develop an 'affective companion' prototype that will provide emotional support to students in the learning process, by helping to alleviate frustration and self-doubt (Burleson, Picard, Perlin, & Lippincott, 2004). Studies carried out by the AutoTutor Group discovered that learning gains correlate positively with the affective states of flow and confusion (Craig, Graesser, Sullins, & Gholson, 2004). According to Fowler's (1997) study, the relationship between learning performance and the arousal is a type of inverted-U curve, and people learn best when their emotions are at a moderate optimal arousal level. Shen et al. (2007) validated this relationship between performance and arousal and revealed that arousal remained relatively stable during learning.

For user emotion modeling, researchers and developers widely refer to Russell's (1980) two-dimension 'circumplex model of affect', where emotions are seen as combinations of arousal and valence (Craig et al., 2004; Fagerberg, Ståhl, & Höök, 2004; Kort et al., 2001; Leon, Clarke, & Callaghan, 2007; Picard, Vyzas, & Healey, 2001). Another model, known as OCC (Ortony, Clore, & Collins, 1990), is also established as the standard cognitive appraisal model for emotions. This model specifies 22 emotion categories based on emotional reactions to situations constructed either as a) goals of relevant events, b) actions of an accountable agent, or c) attitudes of attractive or unattractive objects. Conati and Zhou (2002) used the OCC model for recognizing user emotions in their educational game Prime Climb. Katsionis and Virvou (2005) adapted the OCC model to map students' emotions when they played an educational game. Emotions are also used to design and model learning content. Papert (1996) conducted a project that he described as 'Instead of trying to make children love the math they hate, make a math they'll love'. Participants were involved in designing things-to-learn so as to elicit emotions in ways that will facilitate learning. Other non-educational settings also began to tap into the influence of emotions. For instance, video content with emotion tags were modeled to support the automatic generation of 'video highlights' or personalized recommendations for video films (Hanjalic & Xu, 2005). Sundström (2005) proposed an interesting concept known as an ‘affective loop’, which refers to an affective interaction process or cycle where emotion plays an important role in interaction involvement and evolution.

Emotion recognition is one of the key steps towards affective computing. Many efforts have been taken to recognize emotions using facial expressions, speech and physiological signals (Cowie et al., 2001; Healey, 2000; Picard et al., 2001). The identification and classification of emotional changes has achieved results ranging from 70~98% on six categories of facial expressions exhibited by actors (Bassili, 1979) to 50-87.5% for speech recognition (Nicholson, Takahashi, & Nakatsu, 2000). The successes in physiological emotion detection include Healey (2000)’s 80~90% correct classification for eight emotions, Leon et al.’s (2007) 85.2% for three valence states real-time recognition, Haag et al.(2004)’s 90% for three valence states and Picard et al.’s (2001) 81% for eight emotions. It is suggested however that, because physiological measures are more difficult to conceal or manipulate than facial expressions and vocal utterances, and potentially less intrusive to detect and measure, they are a more reliable representation of inner feelings and remain the most promising way for detecting emotions in computer science.

Pervasive e-Learning Platform is one type of e-Learning platforms that provide “always on” education. It aims to support pervasive learning environments where learning resources and tools could be accessed by students anytime anywhere. It differs from the previous platforms by using wireless computing and pervasive computing technologies. The pervasive e-Learning platform (Figure 1) developed at an online college of a major University in Shanghai delivers fully interactive lectures to PCs, laptops, PDA, IPTV and mobile phones. The core of the platform includes a number of "smart classrooms" distributed around Shanghai, the Yangtze River delta, and even in remote western regions of China such as Tibet, Yan’an, Xing Jiang, and Nin Xia. These classrooms are equipped with smart devices/sensors and specially developed software for distance learning. For example, the touch screen of the room displays presentations (e.g. PowerPoint), while also acts as a whiteboard for handwriting. The instructor can write on materials projected on the screen using a laser E-Pen. To optimize the video quality, a pan-camera can follow the instructor when he/she moves around in the classroom. RFID (Radio Frequency IDentifier) tags are used to identify and track students. Another tracking camera is mounted in the front of the classroom and it captures students’ attention status by recognizing the ‘blink frequency’ of their eyes. During the class session, instructors can load their pre-prepared PowerPoint and Word documents and write on the whiteboard (even when they are away from the whiteboard). The students can also write individual notes on the instructors’ handwriting window. All these classroom activities are being transmitted through various technologies to students at a distance. They are also recorded and archived for later review. Using this hi-tech environment, the teacher can move freely in the room, use his body language to communicate, and also interact with learners naturally and easily as in a traditional face-to-face classroom.

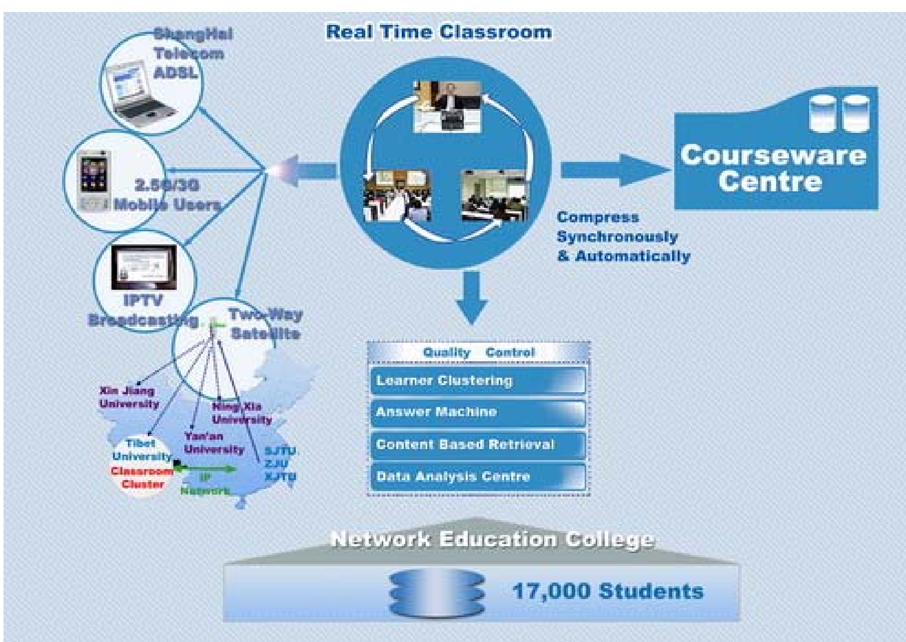

Figure 1. pervasive e-Learning platform in Shanghai

This online college has about 17,000 Students, and 99% of them are working professionals who attend school part time. Therefore, their academic backgrounds, knowledge, and skills vary a great deal. Given such diversity, it is important to provide personalized learning services. The Shanghai system has harnessed data-mining technologies to organize learning communities and provide learning content recommendation based on student profiles (L. P. Shen & Shen, 2005; R. M. Shen, Yang, & Han, 2003). The large number of students in this college and its expansive course delivery systems make it an ideal place to test new and emerging technologies.

Affective e-Learning Models

The goal of this study is to understand how learners' emotions evolve during learning process, so as to develop learning systems that recognize and respond appropriately to their emotional change. This paper also proposes a prototype of an affective e-Learning model that combines learner's emotions with the Shanghai e-Learning platform. As Picard (2004) stated, theories of emotional impact on learning need to be tested and further developed. Until today, there is still a lack of comprehensive and empirically validated theories about emotion and learning. In this experiment, we examined several of the existing emotion theories in learning to help construct our affective e-Learning model. We used Russell's 'circumplex model' to describe user's emotion space. We then used the Kort's 'learning spiral model' as the starting point to explore the affective evolution during learning. Following is the description of these models and our proposal for a prototype of an affective e-Learning model.

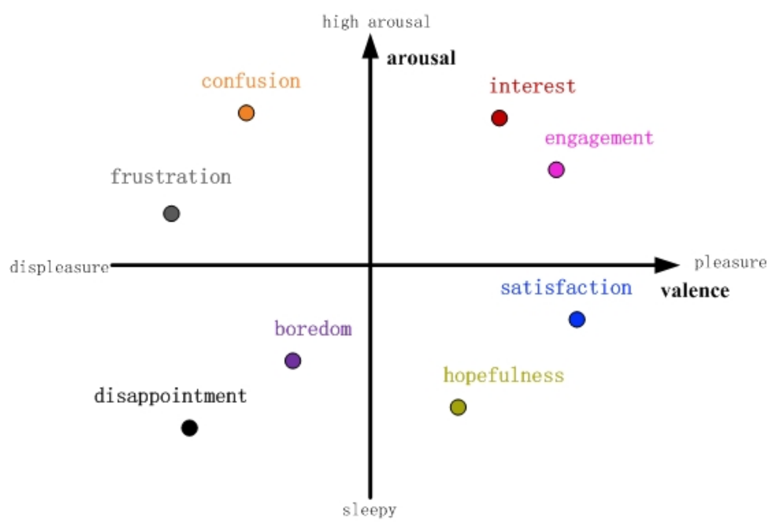

Figure 2. an example of the basic learning emotion space

Russell's Circumplex Model of Affect

In our search for an emotion theory we focused on dimensional models instead of cognitive appraisal model for user emotion modeling because they cover the feeling of emotional experience both on a low level and a higher, cognitive level. One well-established dimensional model is psychologist Russell's circumplex model of affect (Russell, 1980) where emotions are seen as combinations of arousal and valence. In Russell's model, emotions are distributed in a system of coordinates where the y-axis indicates the degree of arousal and the x-axis measures the valence, from negative to positive emotions. The Russell's model is widely used in recent researches (Craig et al., 2004; Fagerberg et al., 2004; Kort et al., 2001; Leon et al., 2007; Picard et al., 2001). And most of these just explored from three to eight basic emotions. Though Kort et al. (2001) proposed five sets of about thirty emotions that may be relevant to learning, however, we believe that skilled human tutors and teachers react to assist students based on a few 'least common set' of affect as opposed to a large number of complex factors; thus, we carefully select a basic learning emotion set which we deem most important for shaping our affective learning model. The basic set includes the most important and frequently occurred emotions during learning, namely, interest, engagement, confusion, frustration, boredom, hopefulness, satisfaction and disappointment. They might not be placed exactly the same for all people when put in the Russell's two-dimension emotion space, because this model focuses on subjective experiences.

Figure 2 is an example of two-dimensional basic learning emotion space. We anticipate revising this emotion set when the study progresses.

Kort's Learning Spiral Model

Kort, Reilly and Picard (2001) proposed a four quadrant learning spiral model (Figure 3) in which emotions change while the learner moves through quadrants and up the spiral. In quadrant I the learner is experiencing positive affect and constructing knowledge. At this point, the learner is working through the material with ease and has not experienced anything overly puzzling. Once discrepancies start to arise between the information and the learner's knowledge structure, he/she moves to quadrant II, which consists of constructive learning and negative affect. Here the learner experiences affective states such as confusion. As the learner tries to sort out the puzzle but fails, he might move into quadrant III. This is the quadrant of unlearning and negative affect, when the learner experiences emotions such as frustration. After the misconceptions are discarded, the learner moves into quadrant IV, marked by 'unlearning' and positive affect". While in this quadrant the learner is still not sure exactly how to move forward. However, he/she does acquire new insights and search for new ideas. Once the learner develops new ideas, he/she is propelled back into quadrant I; thus, concluding one cycle around the learning spiral of Kort's model. As the learner move up the spiral, cycle after cycle, he/she become more competent and acquire more domain knowledge.

Kort, Reilly and Picard (2001) also described the empirical research methods to validate this spiral model, and promised a future paper to report the results of the empirical research. There were some efforts of empirical research on this model, e.g. Kort & Reilly (2002) stated that "we are in the process of performing empirical research on this model", and "ideally, the Learning Companion should observe and try to understand the processes a learner experiences during all of these quadrants; however, this is currently beyond the capabilities of the technology"(Kapoor, Mota, & Picard, 2001) , and "The process of cycling through these emotions during learning is currently being investigated in the present project"(D'Mello et al., 2005). But to our best knowledge, there have been no empirical validation report about this model. We used this ideal learning spiral model as the starting point to explore learner's emotional evolution during the learning process.

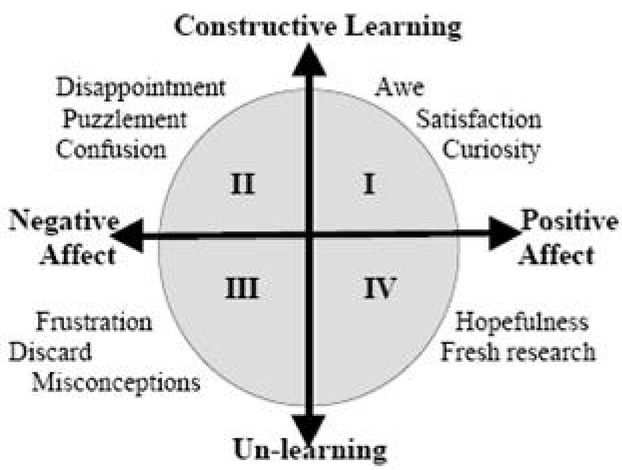

Figure 3. Kort's Learning Spiral Model

The Proposed Affective e-Learning Model

For our study, we used Russell's 'circumplex model' to describe learner's emotions detected from biophysical signals, and used the Kort's 'learning spiral model' as the starting point to explore learners' emotional evolution during the learning process. Finally, based on our previous work (L. P. Shen, Leon, Callaghan, & Shen, 2007; L. P. Shen & Shen, 2005), we proposed a model of affective learning (Figure 4) focusing on how we could make use of the information when we have got the learner's emotion states and their evolution. This affective learning model considers the contextual information of the learner and the learning setting, and generates appropriate responses to the learner, based on his/her emotional states, cognitive abilities, and learning goals. This model can also be used to customize the interaction between the learner and learning system, to predict learner responses to system behavior, and to predict learner's future interaction with the learning system.

The affective learning model used a combination of (a) a cognitive appraisal approach to affective user modeling (which inferences emotions according to situations experienced by the user as well as the observable behavior of the user) and (b) a physiological approach. Figure 4 shows a high-level description of this affective learning model, which only displays the general factors involved. The upper part of the model was modified OCC (Ortony et al., 1990) cognitive appraisal model for emotions, and the lower part of the model was the physiology recognition of emotions, where these two models converge One of the pattern recognition method-Bayesian Networks (Duda, Hart, & Stork, 2000) were employed to model the relations between the emotional states and their causal variables.

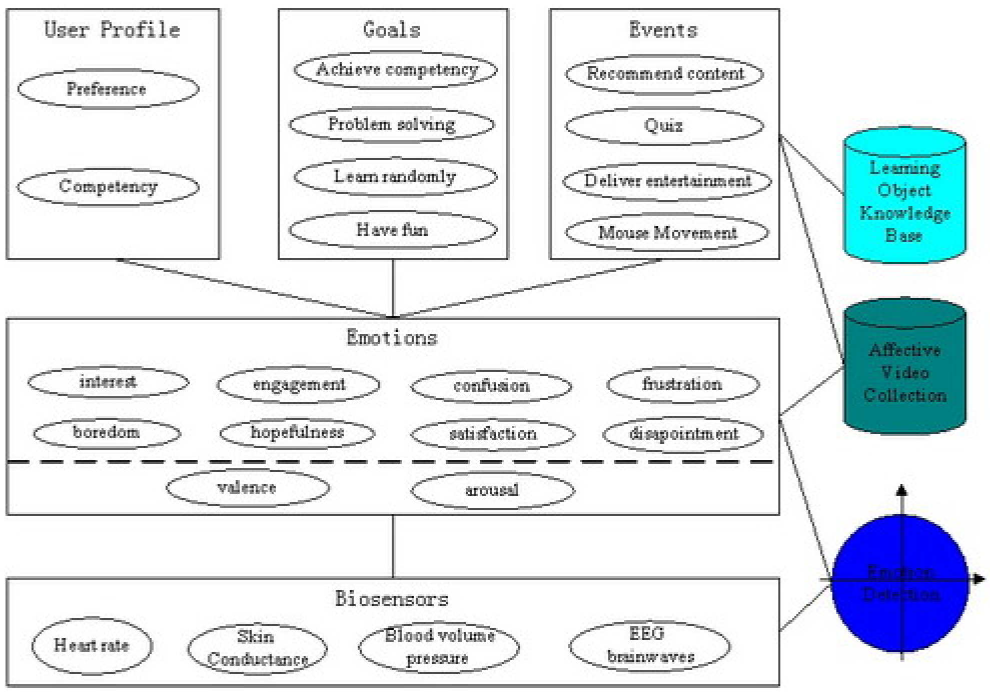

Figure 4. Affective Learning Model

This affective model indicated that the user's emotional states were related to learner profiles (e.g., learning preferences, cognitive skills, knowledge structure), goals of learning, and learner interaction with the learning system. The user's emotional states would in turn influence the measurements of the available sensors. The advantage of having a model based on a Bayesian Network was that it could leverage any evidence available on the variables related to emotional states to make predictions for any other variable in the model. For instance, the user's emotional state could be assessed using existing information on learner profile and the learning context, even in absence of reliable sensors. Or, we could assess both emotional state and learner profile from reliable sensors, learner behavior and system reactions. The emotion detection system helped the system to provide timely help or adequate content based on the emotions the learner is experiencing at a particular moment.

To keep it simple, our model included only a subset of the factors that could be taken into account to assess learner's emotional reactions in e-Learning. This model had the following major components:

1. Learner Profile: only two learner characteristics were considered in this model: learner preference and competency. Learner preference included learning content type (e.g. introduction, examples, cases and exercises), interactive type (e.g. active, expositive and mixed), learning habit (individual, collaborative) and cognitive traits etc. These factors were generated from multiple intelligence theory (Gardner, 1993), which argues that people have differing analytic capabilities, some are good at mathematical equations, others prefer verbal descriptions, and others may prefer to manipulate graphical representations. Information about learner

preference was gathered through data mining technologies and learner surveys, and could also be modified by this learning model dynamically. Learner competency described learner's current knowledge structure, which would be used to compute the learning gap between current and anticipated competencies. This gap analysis was used to identify appropriate learning content that could help the user progress towards his objective competencies.

2. Learning Goals: We identified four types of learning goals for students in Shanghai's e-Learning test bed, that is, an online college that has about 17,000 students. These goals included: acquire-objective-competency, problem-solving, learn-randomly, and have-fun. Our student characteristics survey revealed that these were the common goals of the majority of the students. Among these four goals, the first two were about anticipated events, which the OCC model referred to as 'Prospect Relevant' and that affected the "Prospect Based" emotional category (hope, fear, satisfaction, relief, disappointment), with the other two concerning unanticipated events, which the OCC model refers to as Prospect Irrelevant and that affect the "Well Being" emotional category (joy, distress).
3. Learning Events: We developed three kinds of actions/services to help achieve the learner's goal effectively: learning content recommendation, quiz, and entertainment content delivery (e.g. playing music). The learner's mouse movements were also collected as an indication of engagement or confusion. We had completed a study about learning content recommendation (L. P. Shen & Shen, 2005), an intelligent recommendation mechanism using competency gap analysis and a learning object knowledge base. The entertainment content delivery was included because, when the learners become deeply frustrated or bored, entertainment such as jokes, music and video could help to lift their spirits in the same way as an expert teacher might do in the classroom.
4. Learner Emotions: This affective learning model included eight basic learning emotions: interest, engagement, confusion, frustration, boredom, hopefulness, satisfaction and disappointment, among which the last two emotions are prospect based. The two lower level emotion variables were: valence and arousal.
5. Biosensors: four kinds of physiological data were used in our system: heart rate (HR), skin conductance (SC), blood volume pressure (BVP), and EEG brainwaves (EEG).
6. Learning Object Knowledge Base: The knowledge base included the subject knowledge structure, ontology, learning objects, and an answering machine (R. M. Shen, Han, & Yang, 2002). It also included the affective video collection tool, which stored video clips with emotion tags.
7. The Emotion Detection system gave feed back to the system and helped the system to provide timely help or adequate content for the learner experiencing certain emotions.

The model we described above was used to incorporate the emotion states into the interaction between the learner and the learning system. Emotions could also be feed back to teachers in the classroom and back to the fellows in a team work. Expert teachers are able to recognize the emotional state of their students and respond in ways that positively impact on learning in face-to-face traditional classroom, but in the e-Learning case, there are large numbers of remote students in distributed classrooms and mobile users; thus the challenge is, how could a teacher circumvent this? We would provide a solution for such problems via the real-time feedback of students' emotional states to the teacher that the teacher could then adapt the lecture style, speed and content accordingly. What's more, as emotion plays an important role in interaction involvement and evolution, the teacher should be aware of the students' emotional states when organizing discussion groups so as to enhance the information flow within the group by smoothing the emotion flow.

Experiments and Results

We used the same method as used in the Picard study (Picard et al., 2001), where data were gathered from a single subject over many weeks of time, standing in contrast to efforts that examine many subjects over a short recording interval(usually single session on only one day). Single subject experimental design is a recognized method in educational and psychological research. It is typically used to study the behavioral change an individual exhibits as a result of some treatment (Gay & Airasian, 2003, page 383). Reliability of single subject experiment can be ensured by using reliable instrumentation, repeated measures, and also by describing the experimental conditions in details (i.e., the conditions of measurement and the nature of the treatment) (Gay & Airasian, 2003). Our study carefully followed these guidelines.

Considering the versatility of the variables being studied (i.e., emotion), it seems appropriate to use one-subject design in this preliminary experiment. Ekman and his colleagues (1983) acknowledge that even simply labeled emotions like “joy” and “anger” can have different interpretations across individuals within the same culture. For instance, the same emotion could elicit different physiological patterns from different subjects. For a pilot study, more than one subject will pose great challenge in finding significant physiological patterns. Through repeated measures, this study generated a larger data set than traditional affect recognition studies involving multiple subjects. A repeated measure of one subject in a longer period of time ensured consistent interpretation of the variables (emotions), and also showed the evolution of emotions during the learning process. In addition, in pervasive learning environment, learning is individualized and emotions might be too. The average responses from a group might not apply to individuals.

The subject in our experiments was a healthy male graduate student in the e-Learning lab of Shanghai Jiao Tong University. This experiment focused on gathering physiological data for real-time emotion detection, to explore the affective evolution during learning, and to study the effectiveness of emotion when adding to existing e-Learning platform.

Experimental Method

Collecting reliable affective bio-data can be challenging when comparing to computer vision or speech recognition. Cameras and microphones are reliable and easy to use, but a few factors could affect the reliability of the bio-sensors. For example, whether the subject just washed his hands, how much gel he applied under an electrode, how tight the electrodes were placed, and even the air humidity could affect the readings. What’s more, emotion is often subjective and even the subject might not be completely aware of his own feelings.

We carefully designed the experiment to obtain high quality physiological data for emotion analysis. The experiment was conducted in a learning lab, and continued for two weeks and totally twenty sessions, with each session lasting about 40 minutes. The subject was a senior undergraduate student from computer science department. He sat in the quiet comfortable lab, where he regularly worked and studied. One of his classmates worked in the same lab and helped him when needed, for example, fetching a book because the subject could not move too much with the sensor on, or discussing with the subject when he had some questions. A few other people were nearby but they were quiet and did not interrupt him during the experiment. The subject was preparing for graduate entrance examination, namely, the courses of Data Structure and Object Oriented Programming. He was free to select the learning content, textbooks, exercises, search online, or coding. He was asked to completely focus on studying, and was not allowed to take a break during a single session. During the experiment, his emotion was naturally elicited, responding to the learning situation. Therefore, this research setting was more natural and closer to the real-world settings, comparing to the experiments using guided imaginary technique (Clynes, 1977) and classified emotion picture set (Center for the Study of Emotion and Attention, 2001). In many of their experiments, emotions were initiated by the subjects (that is, subject purposefully elicit emotions such as actors), and might be just external expressions instead of internal feelings. The subject reported his own emotion from the emotion list whenever he felt any change, which was used to label the data. Even though the experiment took place in the subject’s regular place of study, he had some “un-natural” feelings. For example, he was not allowed to move greatly because movement could bring noise into EEG waves through the wired bio-sensors. In addition, he had to remember to report his emotion changes, which he considered as interruption to his learning.

Although our e-Learning model had eight frequently occurred emotions, in this preliminary experiment, we explored four distinctly different emotions: engagement in the quadrant I of Russell two-dimensional affective model (positive valence, high arousal), confusion in quadrant II (negative valence, high arousal), boredom in quadrant III (negative valence, low arousal), and hopefulness in quadrant IV (positive valence, low arousal). The smaller the set, the more likely we are to have greater classification success by the computer.

The data were collected from three sensors: a skin conductance (SC) sensor measuring electrodermal activity from the middle of the three segments of the index and ring fingers on the palm side of the left hand, a photoplethysmyograph measuring blood volume pressure (BVP) placed on the tip of the middle finger of the left hand, and a pre-amplified electroencephalograph sensor measuring EEG activity from the brain whose electrodes were placed on PC_z, A_1 and A_2 according to the *10-20 International System of Electrode Placement*. In our case, three EEG electrodes were sufficient (Lévesque, 2006). Sensors and sampling were provided by the Thought Technologies ProComp5 suite (Figure 5), chosen because the suite was small enough to attach to a wearable computer. Signals were sampled at 256 Hz (namely 256 samples every second). The ProComp5 could automatically compute the heart rate (HR) as a function of the inter-beat intervals of the blood volume pressure, BVP and could also separate different kinds of brainwaves into δ, θ, α, low and highβwith filters. The frequencies and relationships with emotion of each brainwave were listed in Table 1. Each sample of data set comprised 3 raw data (SC, BVP, EEG), the HR from BVP, five brainwaves from EEG, five power percentages of the brainwaves and the label with time tag.

Figure 5. the Subject Wearing ProComp5 in the Experiment

Table 1. brainwaves and their relationship with emotion

Wave Type	Frequency	When wave is dominant
δ Delta	0-4 Hz	Deep sleep
θ Theta	4-8 Hz	Creativity, dream sleep drifting thoughts
α Alpha	8-13 Hz	Relaxation, calmness, abstract thinking
Lowβ Beta	15-20 Hz	Relaxed focus. High alertness, mental activity. Agitation anxiety
Highβ Beta	20- 40 Hz	

We also conducted sixteen 30-minute sessions for emotion-aware (EA) and non-emotion-aware (NEA) content recommendation comparison. During these sessions, we used the emotion detection system introduced following to feedback the subject's emotion states to the content recommendation system and recorded the user interaction (interventions) with the system. In order for the comparison to be as accurate as possible, the two systems were conducted at a pseudo randomly selected sessions and with the same probability. As the result, eight sessions were selected for EA system and another eight sessions were selected for NEA system.

Data Preprocessing

For emotion recognition, we have got 20 sessions, with each session lasting 40 minutes and the sampling rate 256Hz. Finally we select 18 sessions, removing the other two because of the bad placement of the bio-sensors. Then we got a total of 11059200 samples (18 session * 40minutes/session * 60seconds/minutes * 256samples/seconds = 11059200). Such big data set would make data training and data classification very time-consuming. To make it more efficient, and according to the fact that emotion won't change so frequently as much as 256Hz, we merged n samples into 1 sample. When n=256, then we would have 1 sample every 1 second; when n=2048, then we would have 1 sample every 8 seconds. We employed very simple fusion method that we computed the means of the non-oscillating signals (SC, BVP, HR, the power percentages of the 5 brainwaves) and the FFTs of the oscillating signals (EEG, 5 brainwaves from EEG) as the corresponding values of the resulting sample.

Classification and Results

We have got two sample sets for emotion detection: one sample every 1 second (data set I) and one sample every 8 seconds (data set II). And then two pattern classification methods were tested: support vector machine (SVM) and K-nearest neighbor (KNN) (Duda et al., 2000). SVM maps training vectors into a higher dimensional space and then finds a linear separating hyperplane with the maximal margin in this higher dimensional space. The mapping function is called the kernel function. We selected to use the radial basis function (RBF) kernel:

$$K(X_i - X_j) = e^{-\gamma \|X_i - X_j\|^2}, \qquad \gamma > 0 \tag{1}$$

The problem of SVM then requires the solution of the following optimization problem:

$$\min_{w,b,\xi} \quad \frac{1}{2} w^T w + C \sum_{i=1}^{l} \xi_i \tag{2}$$
$$subject \quad to \quad y_i(w^T \phi(x_i) + b) \geq 1 - \xi_i, \xi_i \geq 0$$

Where $K(X_i, X_j) \equiv \phi(X_i)^T \phi(X_j), l$ is the number of samples is in the training set, x_i is the attributes, y_i is the label. By using the software LIBSVM (Chang & Lin, 2007), we first found the best parameter C and γ with cross-validation, then used the best parameter C and γ to train the whole training set, and finally tested over the testing set. KNN was tested with k=1~10 with the function provided by MATLAB (http://www.mathworks.com/).

Results of the classification

The two pattern classification methods: LIBSVM and KNN were tested over the two data sets. Table 2 is the classification results we obtained where we only listed the better results testing on data set I and II. The data shows that when we just used SC, BVP and HR attributes, the rates were 68.1% and 60.3% respectively by SVM and KNN, and when we just used the power percentages of 5 EEG brainwaves, the rates were 67.1% and 62.5%. However, when we used these two groups of attributes together, the rates were as high as 86.3% and 75.2% respectively. We also found that the brainwave power percentages contributed more than the sheer EEG powers from FFT. The best recognition rate 86.3% was achieved by LIBSVM tested on data set I, that is, the data set of one sample every one second. Though other researches have got as high as 90% correct rate over 3 valence levels, we were the very few experiments detecting the real learner's emotions in a natural and close to real world settings. And because emotions won't change too much during learning (L. P. Shen, Leon, Callaghan, & Shen, 2007), it's harder to detect emotions in the learning process.

Table 2. Recognition rates of four learning emotions

Attribute Space	LibSVM	KNN
SC,BVP,HR	68.1% (data set I)	60.3% (data set II)
EEG power% for Brainwaves	67.1% (data set I)	62.5% (data set II)
SC,BVP,HR EEG power% for Brainwaves	86.3% (data set I)	75.2% (data set II)
SC,BVP,HR EEG FFTs	60.8% (data set II)	59.2% (data set II)

Affective Evolution Results

Kort suggested that learning behavior would manifest itself in a spiral-like form i.e. a series of linked cycles separated in time. In order to learn how emotion evolves during learning, we computed the emotion distribution for all the 43,200 samples of data set I (Table 3), where engagement and confusion were the most important and frequently occurred emotions in learning, and frustration was the least. This is consistent with the findings from AutoTutor project (Craig, Graesser, Sullins, & Gholson, 2004). The transition distribution (Table 4) showed that the subject's emotion changed frequently between engagement and confusion in both directions, and then frequently from confusion to boredom. There occurred no loop during single session and one loop within two successive sessions. Of all the 18 learning sessions there were only one loop which could not be used to confirm the Kort's learning spiral model. However, we hoped these initial results would prove encouraging to others who had speculated on this relationship and hopefully would motivate more detailed work on this aspect.

Table 3. the emotion distribution for all the 43200 samples

emotions	sample numbers	percentage
engagement	17625	40.8%
confusion	13738	31.8%
boredom	7992	18.5%
hopefulness	3845	8.9%
Total:	43200	100%

Table 4. the transition distribution for all the 86 emotion transitions

transitions to / from	engagement	confusion	boredom	hopefulness
engagement	×	32	×	×
confusion	18	×	12	3
boredom	1	5	×	6
hopefulness	4	2	3	×

Affective e-Learning Model Results

The affective e-Learning model we implemented was based on our previous intelligent content recommendation work(L. P. Shen & Shen, 2005), and added four emotion-aware recommendation rules as displayed in table 5. We conducted eight 30-minute sessions for emotion-aware (EA) and non-emotion-aware (NEA) content recommendation respectively.

Enhanced user satisfaction is one of the most important objectives of the learning content recommendation system. User satisfaction could be evaluated by analyzing the number of times the user had to interact with the system in order to adjust the content recommended by the system. Manual adjustments meant that the system failed to deliver the content what the user expected and needed at different situations. Experiments indicated the superiority of EA with only 11 user interventions for the entire 8 sessions, whereas NEA was adjusted 21 times, an increase of 91 % (Table 5).

Table 5. the Emotion-aware Recommendation Rules and User Interventions

Emotion states	Rule for that emotion	Number of user interventions	
		EA	NEA
engagement	Normal as NEA according to subject's learning progress and objective	3	21
confusion	Deliver examples or case studies for current knowledge	4	
boredom	Deliver video/music according to subject's preference to ease the tension	1	
hopefulness	Deliver music according to subject's preference to enhance meditation	3	
Total		11	21

Conclusion

Using physiological signals to predict emotions, this study explored the emotion evolution during learning, and proposed an affective e-Learning model. Physiological data were gathered from one subject over many weeks in a natural and close-to-real world setting. The best-case classification rate (86.3%) was yielded by SVM (Support Vector Machine) with raw data, opening up the possibilities for instructors to understand the emotional states of remote learners. When brainwave signals were added to the other peripheral physiological data, the classification rate rose significantly from 68.1% to 86.3%. This increase suggested the close relationship between brainwaves and emotions during learning. When learner emotions detected were feed back to the affective e-Learning model in real-time, the content recommendation system could deliver proper learning content or entertainment content according to learner's current emotional states and other learning contexts. Our experiments indicated the superiority of emotion-aware system over non-emotion-aware system with an increase of 91%, which suggested that using emotional data could greatly improve the performance of e-Learning system, particularly in the categories involving user-centered learning. Other noteworthy findings included that engagement and confusion were the most important and frequently occurred emotions in learning, and that using the power percentages of brainwaves yielded better results than using the sheer FFT powers of brainwaves. Since most current affective learning researches focused on identification of the users' emotions as they interact with computer systems, such as intelligent tutoring systems (Craig et al., 2004) , learning companion (Burleson et al., 2004) or educational games (Conati, 2002). There is a lack of research efforts in detecting emotions during learning in real-time, the emotion evolution during learning and using the emotional feedback to better design e-Learning system. Findings of this study should make a contribution in the research and development of affective e-Learning systems.

While this study has generated encouraging results, it has some limitations. Following are the issues that should be addressed in future studies.

1. Learner's emotions are detected through biophysical signals only. Future studies should use multi-modal pattern analysis of signals, from face, voice, body and learners' surroundings, to achieve more accurate results in emotion recognition.
2. In this study, the subject freely chose his learning content. To better explore emotion revolution during learning, researchers should design well-structured consistent lessons and materials focusing on learning a specific knowledge or course that can be used with more than one subject.
3. The affective e-Learning model resulting from this study was only for self-pace learning, it needs to be broadened to include other 'types' of learning such as classroom lecturing, group discussion etc.
4. The affective e-Learning model we proposed combined emotional feedback with learner profiles and the existing pervasive e-Learning platform. Future studies should explore how to leverage the affective information into the new pedagogical strategies. For example, at which emotion states will the learners need help from tutors and systems (when they are confused or frustrated)? What kind of help do they need at a specific emotion state?

In order to increase the reliability of results, future studies should also include a larger sample. At this exploratory stage, single-subject experiment is more feasible. The value of our work is to confirm a few general principles related to affective learning. And we anticipate a more systematic and in-depth study in the near future.

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