Enhancing Electronic Intelligent Tutoring Systems by Responding to Affective States

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Xiaomei Tao

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Abstract

The overall aim of this research is the exploration mechanisms which allow an understanding of the emotional state of students and the selection of an appropriate cognitive and affective feedback for students on the basis of students' emotional state and cognitive state in an affective learning environment. The learning environment in which this research is based is one in which students learn by watching an instructional video. The main contributions in the thesis include:

- A video study was carried out to gather data in order to construct the emotional models in this research. This video study adopted a methodology in qualitative research called “Quick and Dirty Ethnography”(Hughes et al., 1995). In the video study, the emotional states, including boredom, frustration, confusion, flow, happiness, interest, were identified as being the most important to a learner in learning. The results of the video study indicates that blink frequencies can reflect the learner's emotional states and it is necessary to intervene when students are in self-learning through watching an instructional video in order to ensure that attention levels do not decrease.
- A novel emotional analysis model for modeling student’s cognitive and emotional state in an affective learning system was constructed. It is an appraisal model which is on the basis of an instructional theory called Gagne’s theory (Gagne, 1965).
- A novel emotion feedback model for producing appropriate feedback tactics in affective learning system was developed by Ontology and Influence Diagram

approach. On the basis of the tutor-remediation hypothesis and the self-remediation hypothesis (Hausmann et al., 2013), two feedback tactic selection algorithms were designed and implemented.

The evaluation results show: the emotion analysis model can be used to classify negative emotion and hence deduce the learner's cognitive state; the degree of satisfaction with the feedback based on the tutor-remediation hypothesis is higher than the feedback based on self-remediation hypothesis; the results indicated a higher degree of satisfaction with the combined cognitive and emotional feedback than cognitive feedback on its own.

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Publications

Journal articles

1. TAO, X. & NIU, Q. 2013. Using Ethnography Method to Collect Emotional Data in Affective Learning Research. *International Journal of Information and Electronics Engineering,* 3**,** 216-220.
2. XIAO-MEI, T. & QIN-ZHOU, N. 2013. An emotion classification algorithm based on the blink frequency detection and Bayesian network in affective learning. *Computer Science,* 40**,** 287-291.
3. XIAOMEI, T. & QINZHOU, N. 2015. Study of an algorithm about producing instructional feedback strategy based on an affective learning ontology. *Computer Engineering & Science,* 37**,** 320-328.
4. XIAOMEI, T. & QINZHOU, N. 2015. Study of an algorithm about producing utility optimal instructional feedback tactics based on Ontology and Influence Diagram model in Affective Computing. *Application Research of Computers* 32**,** 427-433.

International conferences

1. XIAOMEI, T., QINZHOU, N., JACKSON, M. & HU, B. A theoretical framework of pedagogical agents based on psychological incentive mechanism and Artificial Psychology theory. IT in Medicine and Education, 2008. ITME 2008. IEEE International Symposium on, 2008. IEEE, 428-433.

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Chapter 1

Introduction

1.1 Statement of the problem

Imagine you are studying a course by watching a video lecture using a computer, while you are engaged and understand the lecture well, the video goes smoothly. When you are confused about a knowledge point in the lecture, the system will stop and suggest that you watch the clip again and start playing from the correct place with your permission. Or the system suggests that you review related clips and relocates the start point at where the prerequisite knowledge point is located. If you feel bored about a trivial knowledge point, the system will suggest that you jump over this clip and begin the next knowledge point. As well as recommending which video clip you should view, the system supports you with emotional feedback. The system responds to you with encouraging, relaxed words when you feel frustrated. The system attracts your attention when your mind begins to wander. The system leaves you alone when you are deeply engaged in learning, and responds to you intelligently in order to maintain you in a positive state and relieve you from negative emotions.

Computer-based lecture videos have become an increasingly popular method for the delivery of distance learning in both higher education and commercial companies. Standard video players interact with users via the control play facilities, such as forward/reverse control, fast and slow motion, and play point relocate etc, but cannot react to the learners' context and provide appropriate learning support. A more satisfactory solution for learning by instructional video involves enhancing the computer system so that it can offer feedback intelligently as a human tutor does in the classroom. An intelligent tutoring system (ITS) can provide direct customized instruction or feedback to students (Psotka, 1988). Human tutors understand learners' cognitive states and emotional states on the basis of their observation and experience. Previous research on traditional ITS, however, is mostly based on a learner's pedagogical state, for example Summary Street (Franzke et al., 2005), Autotutor (Graesser et al., 2005), REALP (Heffernan et al., 2006), eTeacher (Schiaffino et al., 2008), ZOSMAT (Keleş et al., 2009), Help Tutor (Roll et al., 2011). The communication of emotion between the students and the tutors is rarely taken into account.

With the development of Affective Computing (Picard, 1997), it has become possible to enhance an ITS system or e-learning system with emotional intelligence. Affective Computing is defined by Picard (1997) as "computing that relates to, arises from or deliberately influences emotions". Research in Affective Computing encompasses recognizing, interpreting, processing, and simulating human affects. Affective Computing research in the educational field has considered the contribution of emotional factors to e-learning systems. This has led to the development of affective learning systems. Affective learning systems are e-learning systems enhanced with affective abilities in order to recognize the learner's emotional states and respond intelligently. Research into affect recognition has made great progress in recent years (Akputu et al., 2013, Lester et al., 2011, Sariyanidi et al., 2015, TüRker et al., 2014).

This work has demonstrated that it is possible to detect emotional states. The main thrust of the research described in this thesis is not to duplicate previous work but rather to show the way in which knowledge of the emotional state of a student can inform the delivery of material in an e-learning environment.

The overall research hypothesis is: it is beneficial to provide cognitive and emotional feedback when students are in self-learning through watching an instructional video, and to feedback from both cognitive and emotional aspects is better than only using single cognitive feedback.

The research problem set out below considers how to respond to affective states in an affective learning system:

1) Most work in affective computing has focused on the six basic emotions: fear, anger, happiness, sadness, disgust, and surprise (Ekman and Friesen, 1978a). In a learning environment, however, learners rarely experience sadness, fear, or disgust (D'Mello et al., 2007). Even the most widely adopted affective model, the OCC model of emotion (Ortony et al., 1990), does not include many of the affective phenomena observed in natural learning situations, such as interest, boredom, or surprise. So the first problem is to understand which emotions are most important to a learner in learning, including how to represent these emotional states.

2) Most studies that have been done so far have focused on emotion recognition by the interpretation of facial expression, gesture, bio-feedback signals etc. The term 'emotion recognition', however, does not really show what the subject is feeling,

but only a pattern of measurable external changes associated with feelings (Picard et al., 2004). Hence the second problem is to explore what causes such emotional states in a learning environment and how to implement the analysis process by use of a computational model.

3) When the affective analysis is complete, the system needs to produce a response to the learner. There is some indication that positive affect increases intrinsic motivation (Estrada et al., 1994). Minsky (2007) also states, “when we change what we call our ‘emotional states’, we’re switching between different ways to think”. It is, therefore, a vital task in an affective learning system to generate an appropriate response to the learner. The third problem is how to generate the feedback to the learners in an affective learning system.

In summary, there are three research questions in this thesis:

- Question 1: Which emotions are most important to a learner in learning and how to represent these emotional states?
- Question 2: What causes such emotional states in a learning environment and how to implement the analysis process by use of a computing model?
- Question 3: How to use a computing model to generate the feedback to the learners in terms of their cognitive and affective states?

1.2 Research goals

The overall aim of this research is to explore mechanisms which allow us to understand the emotional state of students and how to select an appropriate feedback tactic for the students in affective learning environment. Feedback tactic means a description about how to respond the student, which contains both aspects of cognitive and emotional feedback. A feedback tactic could be a tutorial action such as reviewing the prerequisite knowledge point, or an emotional intervention such as saying encouraging words. In this study, we consider learning by video because it is a universal and low cost way for learning, and it is close to classroom teaching.

This overall aim can be broken down into the following four main sub-goals:

1) To gather data about how students behave when they study by watching an instructional video and how human tutors and students interact with each other in classroom tutoring scenario. This goal is addressed in chapter 3.

2) To develop a method for understanding a learner's emotional state. This goal is addressed in chapter 4.

3) To develop a method for selecting appropriate feedback tactics in accordance with a learner's emotional and cognitive state in an affective learning environment. This goal is addressed in chapter 4.

4) To develop an evaluation system by applying the outcomes of goals 2-3. This goal is addressed in chapter 5.

1.3 Research contributions

With reference to the research sub-goals mentioned above, the following are the contributions that this thesis makes:

1) A video study was carried out to gather data, including the student's emotional states, what causes these emotional states, and how the tutor responds the learners, etc. The video study and its findings will be addressed in detail in chapter 3.

    - This video study adopted a methodology in qualitative research called "Quick and Dirty Ethnography". This approach is capable of providing much valuable knowledge in an affective learnng environment setting in a relatively short space of time.
    - The emotional states, including boredom, frustration, confusion, flow, happiness, interest, were identified as being the most important to a learner in learning.
    - The results of the video study indicates that the blink frequencies can reflect the learner's emotional states and it is necessary to intervene when students are in self-learning through watching instructional video in order to ensure that attention levels do not continue to decrease.
    - The main causes for each emotional state of students in learning and teachers' interpretations about the causes of their activities during teaching are collected. These data collected are used to construct the emotion understanding and feedback models.

2) A novel emotional analysis model for modeling student's cognitive and emotional state in an affective learning system was constructed. The construction and evaluation of the emotion analysis model will be addressed in chapter 4 and 5.

- In the emotion analysis model, a novel method was proposed to classify the emotion into positive or negative state using the eye blink frequency.
- The emotion analysis model is developed via a Bayesian Belief Network (BBN) reasoning approach and it is used to determine the student's cognitive and emotional state while watching an instructional video.
- This Bayesian network is an appraisal model which could deduce the cognitive and emotional state. The construction of this network is on the basis of an instructional theory called Gagne's theory, which divides a learning process into nine instructional steps, and the relationship between each instructional step and its corresponding cognitive state.
- The model was validated using 10-fold cross-validation and the evaluation restult proved that this model can classify negative emotion and deduce the learner's cognitive state.

3) A novel method for producing appropriate feedback tactics in affective learning system was developed by Ontology and Influence Diagram (ID) approach. The ID model is used to select appropriate cognitive and emotional feedback tactics in term of the student's current cognitive and emotional state using utility analysis. The construction and the evaluation of the feedback decision ID model will be addressed in chapter 4 and chapter 5.
    - Considering the affective feedback has impact on the affective and cognitive states in next time slot, the ID model splits affective feedback and cognitive feedback into two time slots respectively and affective feedback is given

before cognitive feedback.

- On the basis of the tutor-remediation hypothesis and the self-remediation hypothesis, two feedback tactic selection algorithms were designed and implemented respectively.
- The evaluation results show that the degree of satisfaction with the feedback based on the tutor-remediation hypothesis is higher than the feedback based on self-remediation hypothesis. And the results indicated a higher degree of satisfaction with the combined cognitive and emotional feedback than cognitive feedback on its own.

1.4 Structure of the thesis

The structure of the thesis is as follows:

Chapter 2:

We introduce the concept of emotion and the representation model of emotion, and discuss the interaction between cognition and emotion in learning. Then, we review the research progress in the field of affective computing and affective learning. In particular, we review the ways of how affective learning systems respond a learner, and discuss modeling techniques.

Chapter 3:

This chapter presents the methodology, experimental design and results of the video study that involves non-interactive and interactive learning environments in a university. Students' behaviors in different contexts are compared. The data collected in the stimulated recall after the interactive learning exercise is used to construct the emotion understanding and feedback models.

Chapter 4:

In this chapter, we introduce the methods for modelling students' cognitive and emotional states, and the methods for selecting appropriate cognitive and emotional feedback in an affective learning system. We use the Bayesian Belief Network and Influence Diagram as the modeling tools, and the data gathered in the video study to construct the emotion understanding model and feedback model.

Chapter 5:

We present the methodology and result of the evaluation study of the video based affective learning system. Given a learning scenario and student's profile, experienced teachers evaluate the feedback tactics generated by the affective learning system.

Chapter 6:

In this chapter, we discuss and analyse the methodology and results in this study.

Chapter 7:

The conclusions are presented and potential future research which extends the work described in this thesis are proposed in this chapter.

Chapter 2

Literature review of basic concepts in general affective learning system

In this section, we overview research related to the study of emotion and cognition, affective computing and affective learning, and how affective learning systems respond to the learner.

2.1 Study of emotion

2.1.1 Emotion in learning

Today, the study of emotion involves diverse fields, such as psychology, cognitive science, computer science, education, neuroscience, engineering, etc., however, there is not an agreed definition of emotion. Kleinginna & Kleinginna (1981) analyzed nearly one hundred definitions related to emotion and reported that emotion is a complex set of interactions among subjective and objective factors, mediated by neural/hormonal systems. In this thesis, the definition from Parkinson & Colman (1995) is adopted, in which they define emotion as "a relatively short-term, evaluative state focused on a particular intentional object (a person, an event, or a state of affairs)". Other terms which have the same meaning are "affective state" or "emotional state", so this thesis uses the terms interchangeably.

Emotion has been identified as a central and essential factor in the teaching/learning process and this must be addressed in the theory and practice of teaching/learning (O'Regan, 2003).With an increase of understanding about how emotional states affect learning, over the last few years, attention has increasingly been drawn to incorporating learners' emotional states into Intelligent Tutoring Systems (ITS). Ekman's six basic emotions (Ekman and Friesen, 1978b), namely fear, anger, happiness, sadness, disgust, and surprise, have been adopted in many affective computing research publications, such as (Black and Yacoob, 1995, Lien, 1998, Hamdi et al., 2012, Das and Bandyopadhyay, 2010). Learning is a process of acquiring new knowledge or skill and the emotions encountered in the learning process have their own characteristics and special meanings. In the learning environment, what emotions are associated with studying?

Pekrun et al.(2002) studied the 'occurrence and phenomenological structures of academic emotions'. The most frequently reported learners' emotional states are anxiety, enjoyment of learning, hope, pride, and relief, as well as anger, boredom and shame. O'Regan (2003) explored the lived experience of students learning online. The emotions specifically identified experienced by students during learning experiences are frustration, fear/anxiety, shame/embarrassment, enthusiasm/excitement and pride. These have a variable effect on the learning process depending on the strength and nature of the emotion, as well as the learning context. Kort *et al.*(2001) proposed the emotion sets possibly relevant to the SMET (Science, Mathematics, Engineering, and Technology) learning process, which includes pairs of anxiety-confidence, boredom-fascination, frustration-euphoria, dispirited-encouraged and terror-enchantment and each pair embracing 6 emotional states from negative to positive states (for example, the pair of anxiety-confidence includes Anxiety, Worry, Discomfort, Comfort, Hopeful, Confident). Craig et al (2004) observed the occurrence of six affective states during learning with an intelligent tutoring system using a manual affect coding system. They analysed frustration, boredom, flow, confusion, eureka and neutral and found significant relationships between learning and the affective states of boredom, flow and confusion. Afzal & Robinson (2006) have derived an emotion set that represents five affective states in learning scenarios: afraid, angry, bored, interested and unsure. D'Mello et al. (2007) confirmed the hypothesis that the basic emotions (anger, disgust) do not play significant roles in learning, the most common states were neutral, confusion, and boredom, and the frequency of occurrence of delight, frustration, and surprise — was significantly lower.

From the literature study above, it can be seen that there is no unified and standard theory or framework to describe the relationship of emotion to learning. For example, there is no consistency in the conclusions reported in the literature, as to whether the emotional state of “anger” appears in learning or not.

On the basis of the statistics analysing to the words describing emotion as they appear in the literature mentioned above, a total of 59 different words describing emotions were counted. After merging of the similar semantic terms, there were 27 different words left. On the basis of the statistical frequency of the occurrence of the 27 words, the words and the frequency of the occurrence ranking in the top 6 respectively are: (Conati and Zhou, 2002). "Flow" means a state of concentration or complete absorption with the activity at hand and the situation (Csikszentmihalyi, 1990), synonymous semantic terms are "calm", "indifference", "insight". The synonymous terms of "happiness" are "delight", "enjoyment", "satisfied", "eureka". The synonymous terms of "interest" are "intrigue" and "curiosity". The synonymous terms of "frustration" are "dispirited" and " disappointed". The synonymous term of "Boredom" is "ennui". The top six emotional states were selected as the emotions to be studied in our research, and those emotional states will be examined by a qualitative methodology which described in Chapter 3.

2.1.2 Representation of emotion

There are two common emotion representation models: categorized emotion representation and dimensional emotion representation(Schröder, 2004).

Categorized emotion representation means using emotion-denoting words, or category labels in human languages to describe emotions. For example, Ekman's six basic emotions (Ekman and Friesen, 1978b), namely fear, anger, happiness, sadness, disgust, and surprise, were mentioned in section 2.1.1.

In the dimensional emotion representation method, the emotions are represented by multidimensional scales. The most common dimensions are pleasure, arousal and dominance (Mehrabian and Russell, 1974), which respectively range from happy to sad, from calm to excited, and from in control to out of control. An emotional state is represented by a PAD (Pleasure, Arousal, Dominance) model with numerical values, for example, angry is coded by {-.51, .59, .25}. A simple but effective method to classify affective states is simply to distinguish between the positive and the negative values (the valence) and react both to absolute values of valence and to changes of valence.

Both representations have been adopted in the affective learning systems. A complete dimensional representation covers all the feeling of emotional experience and eliminates the need for classifying the emotional states into certain categories. The categorical model expresses specific meaning for each state, but the boundary between every two different emotional states has to been drawn by defining the threshold for the observed parameters which measure affective response. Cowi *et al.* (1999) states that emotion categories can be located in an emotion dimension space via rating tests. Schröder (2004) argued that the inverse is not possible, as emotion dimensions only capture the most essential aspects of an emotion concept, they provide an underspecified description of an emotional state. Although we cannot match every emotion representation in the emotion space with a specific category precisely, we can adopt AI techniques to accomplish this classification to a certain extent. For example, Muñoz*et et al.* (2011) uses the Control-Value theory of achievement emotions and employs motivational and cognitive variables to determine an emotion by using Dynamic Bayesian Networks (DBNs). A Dynamic Bayesian Network (DBN) is a Bayesian Network which relates variables to each other over adjacent time steps (Dagum et al., 1995). A Bayesian Network (BN) is a probabilistic graphical model (a type of statistical model) that represents a set of random variables and their conditional dependencies via a directed acyclic graph and it is also called

Bayesian belief network (BBN) (Russell et al., 1995). Chapter 4 will demonstrate how to use a Bayesian Network and learning context information to determine the emotional state and the cause of the emotional state, and also how to use a Dynamic Bayesian Network to model the emotion feedback tactic selection process.

2.1.3 Emotion and cognition in learning

Cognition is mental processes including attention, memory, producing and understanding language, solving problems, and making decisions. Human emotion and cognition are completely intertwined with each other in guiding rational behavior and decision-making (Goleman, 1995, Norman, 1980). Clore & Palmer (2009) state that positive affect tends to promote cognitive, relational processes, whereas negative affect tends to inhibit relational processing, resulting in more perceptual, stimulus-specific processing.

During the learning process, on the basis of Gagne's instructional theory (Gagne, 1965), there is a nine-step process called the events of instruction, and each step correlates to a certain cognitive process. In (Chaffar and Frasson, 2005), the authors proposed some emotional conditions of learning that should exist corresponding to each cognitive process in order to improve learning, such as in the cognitive process of attention, emotional conditions are: avoiding negative emotions, avoiding emotions like joy or sadness that are not related to the learning activity, and inducing the emotion of curiosity by highlighting an element in the interface suddenly.

On the basis of appraisal theory (Roseman and Smith, 2001), emotions are elicited by evaluations (appraisals) of events and situations. And Ortony et al. (1988) proposed an appraisal based model of emotions called the Ortony, Clore and Collins's (OCC) model, which describes the cognitive structure of emotions and have been employed to generate emotions for embodied characters. In the definition in IGI Gloal (2016), "OCC model is a widely used model of emotion that states that the strength of a given emotion primarily depends on the events, agents, or objects in the environment of he agent exhibiting theemotion. A large number of researchers have employed the OCC model to generate emotions for their embodied characters. The model specifies about 22 emotion categories and consists of five processes that define the complete system that characters follow from the initial categorization of an event to the resulting behaviour of the character. These processes are namely a) classifying the event, action or object encountered, b) quantifying the intensity of affected emotions, c) interaction of the newly generated emotion with existing emotions, d) mapping the emotional state to an emotional expression and e) expressing the emotional state."

OCC model provides a clear and convincing structure of the eliciting conditions of emotions and the variables that affect their intensities. In this model, emotions arise from valenced (positive or negative) reactions to situations consisting of events, actors and objects. In a learning process, normally the learners' goal is assumed to be understanding their work, mastering new skills, developing abilities, improving their level of competence, and learning new things. If those goals are achieved, the learner will achieve positive emotional states; otherwise they will adopt negative emotional states.

Phelps (2006) suggested that the classic division between the study of emotion and cognition may be unrealistic and that an understanding of human cognition requires a consideration of emotion. In order to better understand the emotional states and cognitive states, and to select appropriate feedback, it is necessary to consider emotion and cognition in learning together.

2.2 Affective learning

2.2.1 Concept of affective learning

Research in neuroscience and psychology has indicated that emotion plays an essential role in perception, learning and decision making, as it influences cognitive processes (Goleman, 1995). As a consequence, a new sub discipline of Artificial Intelligence, Affective Computing, has been developed. It is defined by Picard (1997) as "computing that relates to, arises from or deliberately influences emotions". Research in Affective Computing encompasses recognizing, interpreting, processing, and simulating human affects. Affective Computing research in the educational field has considered the contribution of emotional factors to e-learning systems (D'Mello et al., 2007, Woolf et al., 2009). This has led to the development of Affective Learning Systems, which are e-learning systems enhanced with affective abilities in order to recognize the learners' emotional states and respond intelligently.

2.2.2 Affective learning systems

With an increase of understanding about how emotional states affect learning, over the last few years, attention has increasingly been drawn to incorporating the learner's emotional state into the Intelligent Tutoring System. In this section of the thesis five affective learning systems will be introduced, they respectively are Prime Climb, Crystal Island, Mentor, Affective AutoTutor, Gaze Tutor.

Prime Climb: Hernández and Sucar (2007) developed an affective behavior model (ABM) for intelligent tutoring systems. The ABM considers the student's pedagogical and affective state, and the affective state is based on the OCC (Ortony et al., 1990) and Five-factor models (Costa and McCrea, 1992). A dynamic decision network (Russell et al., 2009) with a utility measure on both, learning and affect is used to select the tutorial actions according to the pedagogical and affective state. The affective behavior model has been integrated into an educational game to learn number factorization and was evaluated with 22 students whose average age was 12 years.

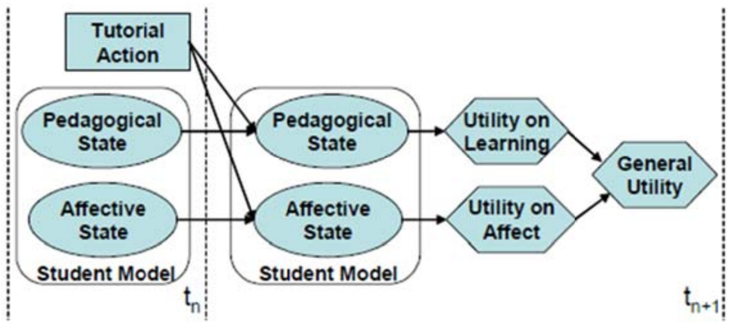

Figure 2-1 High level representation of the dynamic decision network for the affective tutor model (Russell et al., 2009)

The students were arbitrarily divided into two groups of 11 students, the first group played with Prime Climb without the affective behavior model (control group) and the second group played with Prime Climb with the affective behavior model (experimental group). Firstly, each student was given a pre-test to evaluate the prior knowledge of the students on factorization, and then the students played with Prime Climb approximately during 20 minutes. After playing, each student was given a post-test to determine if there was an increase in learning. In the control group the agent instruction was only based on the student pedagogical model. The hints were selected according to the student knowledge about factorization and presented in a speech bubble. With the experimental group, the instruction was based on both the pedagogical model and on the affective behavior model. The hints were still presented through speech bubbles, but they were also accompanied by animations selected according to the affective states of the student. In the control group, the difference between pre-test and post-test was not statistically significant (two-tailed t-test, $p = 0.88$), confirming that students did not learn from the interaction. In the experimental group, the difference between pre-test and post-test was not statistically significant (two-tailed t-test, $p = 0.67$) confirming that, as in the control group, students learned little from the interaction. Although the pre-test to post-test gain for the experimental group was slightly higher than the gain for the control group, the difference is not statistically significant. A possible reason why the difference was not statistically significant was that the students did not play long enough for the ABM to make a difference. In addition, the ABM model has been integrated to an intelligent learning environment for learning mobile robotics and the evaluation results are encouraging since they show a high agreement between the affective state established by the affective student model and the affective state reported by the students(Hernández et al., 2010). But in this evaluation, there was no evaluation about the learning gains using the ABM model.

Crystal Island: Sabourin, J., et al. (2011) present work that investigates the benefits of using theoretical models of learner emotions to guide the development of Bayesian Networks for the prediction of student affect. Predictive models were empirically learned from data acquired from 260 students interacting with the game-based learning environment, Crystal Island. Results indicated the benefits of using theoretical models of learner emotions to inform predictive models. Evaluation of the model showed that the Bayesian Network could predict the emotion label with 25.5% accuracy and could predict the valence of the emotional state with 66.8% accuracy. The Dynamic Bayesian Network could predict emotional state with 32.6% accuracy and valence with 72.6% accuracy.

Mentor: Leontidis et al. (2009) presented a Web-Based Adaptive Educational System to support personalized distance learning, which is named Mentor. The main purpose of Mentor was to support learners' actions during the learning process in an affective way. To achieve this Mentor incorporated an affective module which enhanced the traditional learning practices with an affective dimension. The affective module made use of an ontological approach in combination with a Bayesian Network model in order to provide learners with the correct affective guidance. In total fifty-four students in the field of computer science aging from 18 to 25 participated in the evaluation. The students were given an evaluation questionnaire to fill in where they wrote down their impressions of Mentor. The questionnaire examined the impact of the system in the students' learning process and the satisfaction from students' interaction with the system using three levels, high, medium and low. The results showed that the satisfaction level with Mentor’s interaction at high level is 88% and the satisfaction level with the impact of the system at high level in their learning process is 82%.

Affective AutoTutor: (D'mello et al., 2008, D'Mello and Graesser, 2009, D'mello and Graesser, 2013) There are two versions of AutoTutor that detect and respond to students’ affective and cognitive states (D’Mello et al., 2008, D'Mello and Graesser, 2009). These affect-sensitive versions of AutoTutor, called the Supportive and Shakeup tutors, are collectively referred to as Affective AutoTutor. They used a set of production rules that were designed to map dynamic assessments of the student’s cognitive and affective states with tutor actions to address the presence of boredom, confusion, and frustration. The system used a decision-level fusion algorithm where each channel (conversational cues, face, and posture) independently provides its own diagnosis of the student’s affective state. The major difference between the Shakeup AutoTutor and the Supportive AutoTutor is in the source of emotion attribution. While the Supportive AutoTutor attributed the students’ negative emotions to the material or itself, the Shakeup AutoTutor directly attributed the emotions to the students. Classification accuracies obtained from gross body language were 70%, 65%, 74%, and 72% in detecting boredom, confusion, flow, and frustration versus the neutral baseline (baserate = 50%) (D'Mello, Picard, & Graesser, 2007). Taken together, classification accuracies were 73% when each affective state was aligned with the optimal sensory channel (D'Mello et al., 2008). Machine-learning experiments yielded affect detection accuracies of 73%, 72%, 70%, 83%, and 74%, respectively (chance = 50%) in detecting boredom, confusion, delight, flow, and frustration, from neutral. Accuracies involving discriminations between two, three, four, and five affective states (excluding neutral) were 71%, 55%, 46%, and 40% with chance rates being 50%, 33%, 25%, and 20%, respectively (D'Mello and Graesser, 2009).

D'mello and Graesser (2013) tested the effectiveness of the Affective AutoTutor in promoting deep learning gains in computer literacy sessions with 36 undergraduate students and achieved some positive results. Firstly, the Supportive Tutor consistently outperformed the Shakeup Tutor. Secondly, the Supportive AutoTutor was more effective than the Regular tutor for students with a low level of prior knowledge (low and high median split on pretest scores) in the second session, but not the first session. Participating in the second session on a related subject matter might cause interference with acquired knowledge in the first session. So, the tutor should be supportive to these students when there has been enough context to show there are problems. Thirdly, low prior-knowledge students learned significantly more from the Supportive AutoTutor than the Regular tutor, while the students with more knowledge did not benefit from the Supportive AutoTutor. These students with more knowledge did not need the emotional support, but instead they needed to go directly to the content.

Gaze Tutor: D'Mello et al.(2012) developed an intelligent tutoring system (ITS) that aims to promote engagement and learning by dynamically detecting and responding to students' boredom and disengagement. The tutor used a commercial eye tracker to monitor a student's gaze patterns and identify when the student was bored, or disengaged. The tutor then attempted to reengage the student with dialog moves that directed the student to reorient his or her attentional patterns towards the animated pedagogical agent embodying the tutor. The efficacy of the gaze-reactive tutor in promoting learning, motivation, and engagement were evaluated in a controlled experiment where 48 students were tutored on four biology topics with both gaze-reactive and non-gaze-reactive (control condition) versions of the tutor. The results indicated that: (a) gaze-sensitive dialogs were successful in dynamically reorienting students' attentional patterns to the important areas of the interface, (b) gaze-reactivity was effective in promoting learning gains for questions that required deep reasoning, (c) gaze- reactivity had minimal impact on students' state motivation and on self-reported engagement, and (d) individual differences in scholastic aptitude moderated the impact of gaze-reactivity on overall learning gains.

Besides the affective learning systems presented above, more research work about incorporating the learner's emotional states into the Intelligent Tutoring System is presented briefly. Kort *et al.* (2001) proposed a comprehensive four-quadrant model that explicitly linked learning and affective states. They used this model in their affective learning companion, a fully automated computer program that recognized a learner's affective state by monitoring facial features, posture patterns, and onscreen keyboard and mouse behaviours. Conati (2002) proposed a probabilistic system which tracked a learner's emotions during interactions with an educational game. Her system relied on dynamic decision networks to assess the affective states of joy, distress, admiration, and reproach. Lahart, Kelly & Tangney (2007) described a system called P.A.C.T., which provides personalised coaching for parents in their role as home tutors. P.A.C.T. endeavoured to coach parents in a set of tutoring strategies that provided a mechanism to positively influence the emotional state of the child therefore enhancing the learning process. Yusoff & Boulay (2010) described an affective tutoring system that added an emotion-focused strategy to a standard problem focused strategy in order to help students better regulate their emotional states. Lin et al. (2014) developed a novel ATS which included four modules: affective recognition (combines facial emotion recognition and semantic emotion recognition), tutor agent, content, and instruction strategies for examining the influence of ATS in Accounting remedial instruction on learning effectiveness and usability.

Emotion recognition is a key technology underpinning the systems mentioned in the previous paragraphs. The learners' affective states are recognized by various sensors, which can capture postural, facial, skin-surface, and gesture changes (Picard *et al*, 2004). Emotion recognition is only the first step in an affective learning system. The job of the computer in recognition, however, is to assess a constellation of such patterns and relate them to the user's affective state.

The term ‘emotion recognition’ does not, therefore, refer to a system which identifies what a subject is feeling, but only a pattern of measurable external changes associated with feelings (Picard et al., 2004). Most research omits further emotion interpretation but responds to the emotion directly. The causes of the emotion are complicated, for example, given the one emotion of “boredom”, there may exist two completely different causes, a too difficult challenge or a too easy challenge. Chapter 4 will discuss how to interpret emotion in the learning environment using an emotion analysis model.

Here, Table 2-1 is an overview of existing systems.

Table 2-1 Overview of existing systems

System	Summaries of the existing system
Prime Climb	Prime Climb is an instructional game to learn number factorization which could be integrated with an affective behavior model (ABM). The ABM is a dynamic decision network which could select the tutorial actions according to the pedagogical and affective state. It was evaluated with 22 students whose average age was 12 years. The pre-test to post-test gain for the experimental group was slightly higher than the gain for the control group, the difference is not statistically significant.
Crystal Island	Crystal Island is a game-based learning environment, in which student's emotional state could be predicted by Bayesian Networks. the Bayesian Network could predict the emotion label with 25.5% accuracy and could predict the valence of the emotional state with 66.8% accuracy. The Dynamic Bayesian Network could predict emotional state with 32.6% accuracy and valence with 72.6% accuracy. The data used in this research were collected from 260 students.
Mentor	Mentor is a web-based adaptive educational system to support personalized distance learning. The affective module made use of an ontological approach in combination with a Bayesian Network model and provided the cognitive and emotional feedback to the students. In total 54 students in the field of computer science aging from 18 to 25 participated in the evaluation. The results showed that the satisfaction level with Mentor's interaction at high level is 88% and the satisfaction level with the impact of the system at high level in their learning process is 82%.
Affective AutoTutor	Affective AutoTutor takes the individualized instruction and human-like interactivity to a new level by automatically detecting and responding to students' emotional states in addition to their cognitive states. Machine learning techniques were used to classify students' affective states. A set of production rules were used to map the input parameters with appropriate tutor actions. Affective AutoTutor was tested with 36 undergraduate students in promoting deep learning gains in computer literacy sessions and achieved some positive results.
Gaze Tutor	Gaze Tutor is an intelligent tutoring system (ITS) that aims to promote engagement and learning by dynamically detecting and responding to students' boredom and disengagement. The tutor used a commercial eye tracker to monitor a student's gaze patterns and identify when the student was bored, or disengaged. The efficacy of the gaze-reactive tutor in promoting learning, motivation, and engagement were evaluated in with 48 undergraduate students. The results indicate that gaze-sensitive dialogs were successful in dynamically reorienting students' attention patterns to the important areas of the interface.

2.3 “Teacher immediacy” and “student immediacy”

The term ‘immediacy’ was first described by social psychologist Albert Mehrabian (Mehrabian, 1969) as ‘those communication behaviours that enhance closeness to, and nonverbal interaction, with another. Andersen (1979) later described immediacy as a nonverbal manifestation of high affect, demonstrated through such strategies as maintaining eye contact, leaning closer, and smiling. Teacher immediacy behaviours were further developed by Gorham (1988) to include verbal behaviours such as responding promptly, praises students' work, actions or comments, uses humor in class, addressing students by name, and using personal examples. Today, the term ‘instructional immediacy’, rather than ‘teacher immediacy’ is used in connection with the online environment (Walkem, 2014). It includes those behaviours that an instructor takes to increase students’ sense of human interaction, instructor presence, caring and connectedness (Kim and Bonk, 2010).

Plax et al. (1983) states that students' perceptions of teachers' selective use of Behavior Alteration Techniques (BATs) and teachers' nonverbal immediacy were shown to be associated with students' affective domain of learning. And a linear combination of teacher nonverbal immediacy and BAT use was shown to be positively related to student’s affective domain of learning. The affective domain of learning refers to students' attitudes, beliefs, and values toward the subject matter and learning experience (Bloom, 1956) .

Although teacher immediacy has received considerable attention, there is a large gap in instructional research regarding students’ immediacy behaviors (Baringer and

McCroskey, 2000). In (Rosoff and Morganstern, 1980), feedback was categorized as being either negative (students providing no behavior enhancement) or positive (students providing enhanced behaviors or nonverbal agreement). Feedback was described as specific nonverbal immediacy behaviors, including positive head nods, eye contact, attentive postures, and repeated interactions or questions during and after class. These student behaviors were hypothesized to express agreement, approval, and interest in the teacher and the material being presented.

The online teaching environment requires different immediacy behaviours from those witnessed in conventional classrooms (Kim and Bonk, 2010). A number of studies have been undertaken to identify key immediacy behaviours in the online environment (Walkem, 2014). These include the use of humour (Gorham, 1988), addressing students by name in correspondence (Gorham, 1988), the sharing of personal experiences (Gorham, 1988), responding promptly to students (Gorham, 1988, Kim and Bonk, 2010), and posting introductions that include pictures and appropriate personal and professional information (Kim and Bonk, 2010).

The detection of student immediacy and the delivery of teacher immediacy can be accomplished in an affective learning environment by current techniques. This research focuses on how to understand student immediacy and deliver teacher immediacy when the student is learning by watching instructional video.

2.4 How an affective learning system responds to a learner

2.4.1 Event-driven feedback and emotion-driven feedback

On the basis of the literature review, affective learning systems have different types of feedback mechanisms. Some systems respond to learners when the learner has an interaction event with the system, this type of feedback is called event-driven feedback. For example, if a learner gives an answer in a question-answer activity, the system responds to the learner in terms of the answer state. The system responds to the learner with congratulation when the learner gives a correct answer, or encourages the learner to try again when the learner fails. Underpinning this type of feedback, the system predicts the learners' emotional state using an appraisal model, such as OCC (Ortony et al., 1990). Systems adopting this feedback driven mechanism include (Hernández et al., 2006, Lester et al., 2011, Heylen et al., 2004, Jaques et al., 2004, Leontidis et al., 2009). This type of system normally instructs students using a series of activities, and questions and answers. In contrast, some systems respond to the learner when they detect the learner's emotional state, this is called emotion-driven feedback. This type of feedback could appear at any time during the learning process not just when there is an event. For example, when the system detects that a learner shows confusion when trying a task, it responds to the learner with a hint. As to this type of feedback, the learning activities could be various, such as reading, thinking, watching video, etc. The emotion recognition techniques normally are on the basis of the learners' facial expression, gesture, bio-signal, voice, text, etc. The learners' emotional state could be detected in real time. The systems adopting emotion driven feedback include (Li and Ji, 2005, D'mello et al., 2008, D'Mello et al., 2012, Sarrafzadeh et al., 2008, Liao et al., 2006).

Event-driven feedback essentially uses an event to predict emotion and its intrinsic limitation is that the system is triggered only when there is an event. In fact, learners need support not only when they interact with the system, but also during their learning process. The response to a learner when he feels very confused, such as a hint, is helpful to prevent the learner descending into more negative emotion caused by failure. The advantages of event-driven feedback are obvious and listed below:

- The reason why an emotional state appears can be inferred by the appraisal model, and this is very helpful for providing appropriate feedback;
- The learner will not feel offended during the learning process, especially whilst deep thinking.

Emotion-driven feedback could provide feedback at any time during the learning process. The learner could receive support before they believe they have failed, and this type of anticipatory feedback is very important for preventing a negative state to appear and supporting a learner’s confidence. Nevertheless, it is inadvisable to provide feedback every time when an emotional state changes, so the opportunity for feedback still needs to be selected carefully. In addition, emotion-driven feedback has the limitations below:

- The emotion recognition needs extra facilities and software to support it, such as camera, EEG sensor, Galvactivator skin conductivity sensor, etc., and most of these are intrusive;

- The cause of an emotional state cannot be identified in the emotion recognition process, further analysis incorporating the learning context is necessary.

These two feedback driven methods have their own advantages and disadvantages, but could be inter-complementary. They could be integrated in a system, which is able to respond to learners when there is an event with event driven feedback, and respond to learners when their emotional state changes using emotion driven feedback.

2.4.2 Affective and Cognitive feedback tactics

Feedback tactics are a description of how to respond to a learner in a tactical view rather than an operational view. For example, "review the prerequisite knowledge point" is a description in tactical view, and "review the definition of Matrix" is a description in operational view. Cognitive feedback is common in e-learning systems, which respond to learners by providing cognitive instructional material, such as hints, examples, etc. Affective feedback tactics mean a description of how to respond to a learner by emotion elicited material, such as via a humorous video, encouragement, etc. The goal of both tactics is supporting the learners during the learning process. The effects on learners' cognition and emotion from those feedback tactics are intertwined due to the interrelationship between cognition and emotion. Cognitive feedback could provide the cognitive support to the learner, and this will indirectly influence a learner's emotional state. For example, hints could help a learner to succeed in a task and this will cause a positive emotional state in the learner. On the other hand, emotion feedback could provide the emotional support to a learner, and a positive emotional state could facilitate the development of cognition. On the basis of the interrelationship between cognition and emotion, a model of learners' cognition and emotion was proposed in Figure 2-2. The main difference between the model in Figure 2-1 and the model in Figure 2-2 are: the model in Figure 2-2 describes the causal relationship between cognitive state and affective state; affective feedback is included in the model independently.

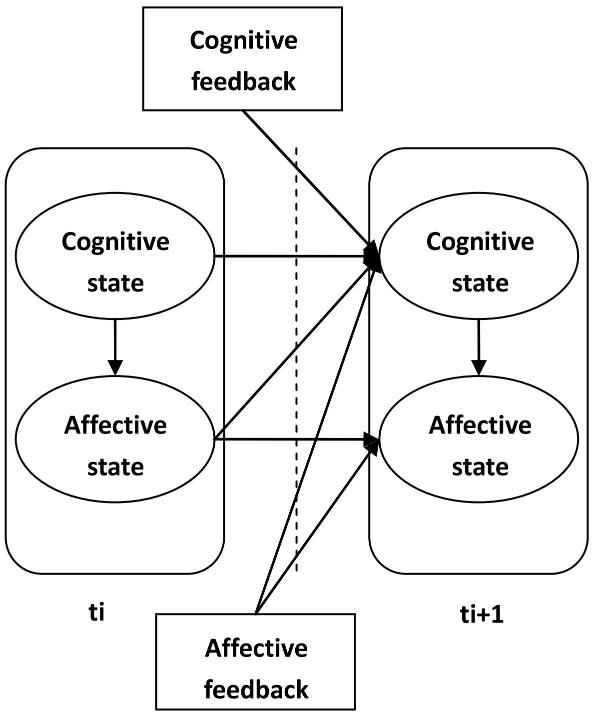

Figure 2-2 A learner's cognition and emotion model

There is no consistency in the literature on the terms used for affective and cognitive feedback, in (Robison et al., 2009b), they are called task-based and affect-based feedback, and in (Yusoff and Boulay, 2010), they are called emotion-focused strategy and problem focused strategy.

The common feedback tactics used in affective learning systems (Boulay, 2011, D'mello et al., 2008, Hernández et al., 2006, D'Mello et al., 2012, Lahart et al., 2007, Arroyo et al., 2007, Liao et al., 2006, Murray and VanLehn, 2000, Murray et al., 2004, Lester et al., 2011, Robison et al., 2009b, Woolf et al., 2009, Sarrafzadeh et al., 2008, Heylen et al., 2004, Jaques et al., 2004, Leontidis et al., 2009) are classified as follows. The affective feedback tactics are:

Positive affective feedback tactics: empathetic statement, encouraging statement, game, praising students' effort, acknowledging students' emotion, adding interest and excitement, meta-cognitive response about students' progress and about good learning habits.

Concerning "meta-cognitive response about students' progress and about good learning habits", for example, "Congratulations! You are getting more questions right than before.(Woolf et al., 2009)"

Negative affective feedback tactics: warning statement.

Neutral affective feedback tactics are: getting attention, requesting emotional information from the student, links performance to student effort and attributes failure to external issue and success to internal issues.

Concerning, "links performance to student effort and attributes failure to external issue and success to internal issues", for example, we will use external responses ("That problem was really hard") when students of low self-concept (self-concept means assessment of current performance in a discipline, which is related to academic outcomes and motivation (Narciss, 2004)) fail, and use internal responses

("Congratulations, you did an amazing job with that!") when they succeed, hopefully reversing their negative beliefs (Woolf et al., 2007) .

The cognitive feedback tactics are: make the task easier, make the work more challenging, give a lesson about a basic concept, give a lesson about a sub-topic, give a lesson about a new topic, repetition, review, ask a question, discussing problems or solutions, give hints, answer questions, show-new-skills.

Most of the systems cited here do not have a clear boundary between affective feedback and cognitive feedback, which are normally combined as pedagogical tactics. Or use different dimension to describe feedback tactic, for example, Auto Tutor (D'mello et al., 2008) incorporates this 5 dimensional assessment of the student and responds with: (a) feedback for the current answer, (b) an empathetic and motivational statement, (c) the next dialogue move, (d) an emotional display on the face of the AutoTutor embodied pedagogical agent, and (e) emotionally modulating the voice produced by AutoTutor's text to speech engine. Only the research work in (Yusoff and Du Boulay, 2009, Yusoff and Boulay, 2010) classify affective feedback and cognitive feedback (called emotion-focused strategy and problem focused strategy in their study)and evaluated the system with and without affective tactics. The affective feedback undertaken in (Yusoff and Du Boulay, 2009, Yusoff and Boulay, 2010) was a shorter version of Benson's relaxation techniques (Benson et al., 1999) which concentrated on the upper limbs only.

In the literature, some principles of feedback have significance on the rule design, for example, praising effort rather than correctness of response, linking performance to student effort and attributing failure to external issues and success to internal issues, immediate feedback for students with low achievement levels in the context of either simple (lower-level) or complex (higher-level) tasks is superior to delayed feedback, delayed feedback is suggested for students with high achievement levels, especially for complex tasks (Woolf et al., 2007, Woolf et al., 2009).

2.5 Summary

The literature review in this chapter introduced the inter-relationship between emotion and cognition in learning, the existing Affective Learning Systems, and focused on how the system responds to learners from practical and technical aspects. The emotion set {boredom, frustration, confusion, flow, happiness, interest} is selected for further research work on the basis of the analysis of the literatures. The 'emotion recognition' models in most existing systems only identify a pattern of measurable external changes associated with emotions. The existing systems do not interpret learners' emotional states with an independent model but respond to the emotion directly, so this interpretation work is weak. Without a step to understand the cause of a learner's emotional state, the effect of the feedback model will be limited. It is necessary to deduce what emotional states appear during learning process, and model the emotion interpretation process and feedback process. How to understand a learner's emotion and how to respond to learners on the basis of the cause are the main objectives of our study which will be discussed next.

Chapter 3

Background study

How do students behave when learning via an instructional video? What emotional states do students experience and why? How do teachers respond to students in classroom teaching? In order to answer these questions, two video studies were designed to investigate the characteristics of two types of interactions in learning: non-interactive environments and interactive environments. In the former the students learn by themselves via watching an instructional video, and in the latter the students were taught by a human tutor.

This chapter presents the methodology, experimental design and results of the video study that involves non-interactive and interactive learning environments in a university. Students' behaviours in different contexts are compared. The data collected in the stimulated recall after the interactive learning exercise is used to construct the emotion understanding and feedback models.

3.1 Experimental design

3.1.1 Methods

The methodology adopted was "Quick and Dirty Ethnography" (Hughes et al., 1995). This 'quick and dirty' approach is capable of providing much valuable knowledge of the social organisation of work of a large scale work setting in a relatively short space of time. There is a trade-off between the efficiency and the completeness in this methodology. Fieldworkers adopting this approach undertake short focused studies to quickly gain a general picture of the setting. In this research, instead of a large scale study, a total of 15 students, 2 tutors, 4 sessions were used to explore how emotion works in learning generally. There are two teaching/learning environments in the observation study, non-interactive environments and interactive environments. The conditions of the observation experiment are summarized in Table 3-1.

Table 3-1 The experimental conditions

	Non-interactive environments		Interactive environments	
	Session 1	Session 2	Session 3	Session 4
Participants	Student 1~student 5	Student 1~student 5	Student 6~student 10, Tutor A	Student 11~student 15, Tutor B
Learning style	The students watched an appointed instructional lecture video	The students watched an appointed instructional lecture video	The tutor taught the students by a lecture	The tutor taught the students by a lecture
Learning content	Array	Array & pointer	Array & pointer	Array & pointer
Stimulated recall	no	no	yes	yes
Session length	30 mins	32 mins	40 mins	35 mins

3.1.2 Non-interactive environments

3.1.2.1 Aims of the experiment

The observational experiment in the non-interactive environment is designed to determine how the students behave when they learn through watching an instructional video by themselves.

3.1.2.2 Subjects

There were five participants in the non-interactive environment, 1 female and 4 males. All the subjects were junior students at Guilin University of Technology, China. Their major was Physics, their ages ranging from 20 to 22. The students were selected randomly from volunteers. Demographics including age, gender and major were collected from the students when they applied to participate in the experiment.

3.1.2.3 Experimental settings

The students watched the instructional video as a group, but independently. They each had a PC that was used to display the video they watched and to record their responses (via a web camera) at the same time. The web cameras used in the experiments were mounted on stands, operating at the frame rate of 15 fps., with a resolution of 320×240 px. They were set on the desk next to the monitor, aimed at the student, so as to that they could capture any upper body movement. The participants wore earphones to hear the tutor's voice. They were required to make a hand gesture at the start point (for synchronization purposes) and were not able to control the operation of the video during the session. This constraint was necessary to synchronize all the students' videos and the instructional video. Students were spatially separated in the room so as to reduce the amount of inter-student interaction.

3.1.2.4 Instructional content

The content for session 1 was material on computer main memory storage using an array. This was relatively basic and included topics such as array declaration, initialization and usage. The content for session 2 was more advanced and explained how pointers could be used to operate on elements in an array.

3.1.2.5 Procedure

The main steps of this study are presented as follows:

1) Introduction of the aims of this study to the students and completion of the consent form.
2) The participants were invited to watch an instructional video about the C programming language which lasted about 30 minutes.
3) The upper parts of the participants' body were video recorded while they were watching the video.

The procedure was repeated in session 1 and session 2, with the same participants but with different learning content. These two sessions were taught by the same tutor, and the tutor's face did not appear in the video, only his voice and his computer screen were recorded. His computer screen was used to display the slides and the program implementation.

3.1.3 Interactive environment

3.1.3.1 Aims of the experiment

The interactive environment was designed to collect the interaction between the students and the tutor, the students' emotional states, what causes these emotional states, and how the tutor responds the learners.

3.1.3.2 Experimental settings

The web camera settings were the same as in the non-interactive environment. We added two cameras which were used to capture the overall view from the back and front. All the five students sat in front of the tutor, so that they could communicate face to face. In the lecture, the tutor displayed the slides and executed code on a computer, and the output on the screen was broadcast to the five students' computer screens. The screens of the student's computers were synchronized with the tutor's computer screen, and the students could not operate their own computers.

3.1.3.3 Instructional content

In the interactive environment, the content was the same as in session 2. The reason why we selected this content was because the variation in the knowledge difficulty level in this section was more marked and this could cause a more obvious variation in the students' emotion.

3.1.3.4 Subjects

The participants in the experiments in interactive environment totaled 10 students and 2 tutors, with 5 students and 1 tutor in each session. In session 3, the participants included 1 female tutor, 1 female student and 4 male students, and in session 4 the participants included 1 male tutor, 2 female students and 3 male students. The students were freshmen studying majors in Computing and the tutor who taught them in the experimental sessions was also the one who taught them in the class. The students and their demographics were collected in the same way as in the non-interactive environment experiment.

3.1.3.5 Procedure

The main steps of this study are presented as follows:

1) Introduction of the aims of this study to the students and completion of the consent form.
2) Teaching session. Started the video capture. The facial expressions of the students and their upper bodies were video recorded. The screen of the tutor's computer, the tutor's voice and the tutor's upper body were recorded.
3) Stimulated recall. After the teaching process, the students and tutors were asked to review and interpret the video.
4) Debrief meeting within the research team and the tutor team.

The procedure was repeated in these two sessions, with the same learning content but different participants. These two sessions were held after the teaching session about pointers, which was one of the previous sections. The two tutors used different instructional methods to teach, although the teaching content was the same. The teaching style of the female tutor in the session 3 encouraged self-discovery. She asked the students questions to help them to recall prior knowledge, and asked them to predict what would happen next. The male tutor in the session 4 was humorous, his style involved the introduction of some light-hearted topics into the session. He asked the students fewer questions than the female tutor when delivering content but he introduced three comprehension problems to the students as classroom exercises.

In the stimulated recall, which took place after the teaching session, the students were required to identify their emotional states and when the emotional state started and ended. The emotional states could be one state of {happy, interest, flow, boredom, confusion, frustration} or the students could describe it with other words if they could not find a suitable word in these six states. The description of the six emotional states and the procedure for selecting them can be found in chapter 2.1.1. The tutors were asked to recall and describe their teaching activities and why they selected a certain teaching activity.

3.2 Data processing

In the data coding work, a video analysis tool called Elan[1] was used. Elan has a number of facilities such as segmenting the videos, tagging the segment, playing in slow motion, synchronizing videos and so on. In the observation of the

[1] http://www.lat-mpi.eu/tools/elan/

non-interactive environment, we obtained 10 video files with a complete duration of 310 minutes for session 1 and session 2, each involving 5 students and the study time was 30 and 32 minutes respectively. In the observation of the interactive environment, we obtained 10 student's video files totaling around 375 minutes length for session 3 and session 4, each involving 5 students and the lecture time was 40 and 35 minutes respectively. One additional video file in the interactive environment is used to record the whole scenarios in full view which is used to be supplement if the single video cannot supply enough information.

3.2.1 Processing the data in the students' video

All of the videos (excluding the full view video) were analysed and an interesting phenomenon was found. It was noted that the blink frequency of the subject varied with respect to the teaching content. After further literature research, this phenomenon was noted as being reported in a number of psychological studies. The Blink-hedonia hypothesis proposed by Tecce (1992) states that decreased blink frequency is related to pleasant feelings, whereas an increased frequency of blinks accompanies unpleasant mood states, such as nervousness, stress and fatigue. Tanaka & Yamaoka (1993) investigated the relationship between task difficulty and blink activity, which includes blink frequency, blink amplitude, and blink duration. The results indicated that in a mental arithmetic task, the blink rate for a difficult task was significantly higher than that for an easier one, but in a letter-search task, the blink frequencies were not influenced by the difficulty of the task. Blink frequency is therefore related to not only task difficulty but also the nature of the task. There are tasks where blink frequency varies and tasks where blink frequency does not vary. Where blink frequency does vary, higher blink frequency indicates a higher task complexity. In contrast, blink amplitude and blink duration showed no systematic relationship to task difficulty. Further, for visual tasks, such as a reading task, the research by Cho *et al.* (2000) indicated that in visual tasks mean blink frequency was affected by the position of gaze and not the level of task difficulty. In visual tasks, the nature of the visual task was the predominant factor which affects the blink frequency. On the basis of the literature, blink frequency, task difficulty level, emotion and event type were selected to code the videos.

The students' facial expressions, upper body gestures and voices were recorded. In the process of data coding and analysis, we used two indexes to code the students' videos, one was blink frequency, namely the blink count per minute, and another one was the number of body movements per minute. The body movement count includes changes of facial expression, body movement, head movement and thinking aloud. The average number of movements per minute was calculated using *the total body movement number/the total minute number*.

As the results in (Drew, 1951, Doughty and Naase, 2006) predicted, the average blink frequency varies greatly between individuals in our experiments, for example, in session 2, the average blink frequency varied from 10.61 to 76.39 per minute. To enable a comparison, we used the process set out below to analyse the data:

1) To normalize each student's blink frequency so that the blink frequency only

varies between 0 and 1. In the normalization procedure, for each $student_i$, we took the maximum values of blink frequency as the divider max_i, and then divided blink frequency in every minute $blink\_frequency_{ij}$ into it, namely $blink\_frequency_{ij} / max_i$ (j ranges from 1, 2, … to n, denoting the duration in minutes).

2) To average the normalised blink frequency of five students in each session, and this value is called AN blink frequency.
3) To normalize the AN blink frequency by using the maximum value of AN and this value is called NAN blink frequency which is between 0 to 1.

3.2.2 Processing the data in the instructional video

The instructional videos were divided into segments in terms of different instructional events, and each instructional event was marked with a number from 1 to 5 to represent the difficulty level of this event. The difficulty level of the event was determined by the difficulty level of the corresponding knowledge point and the type of the instructional event. The difficulty level for each knowledge point was graded on the basis of the tutor's experience. We listed the knowledge points which were taught or reviewed in the instructional video and asked three tutors, all who had an extensive experience of C programming, to rank the difficulty level from 2 to 5 for each knowledge point independently. A higher score indicated a higher perception of difficulty. In each case the difference in the tutors' scores for the same knowledge point were within one level. We selected the score that was agreed by at least two tutors. With regard to the task type, on the basis of the observation of the instructional video, we summarized the type of the instructional events in Table 3-2. For example, if the difficulty level of a concept was 2, and this concept was reviewed in the beginning of the session, then the difficulty level of this event is 1 applying the coding rule “reviewing an old knowledge point”, the difficulty level of the event equals the difficulty level of the corresponding knowledge point -1.

Table 3-2 Coding rules for the difficulty of the events

The type of the instructional event	*The difficulty level of the event*
delivering a new knowledge point	The difficulty level of the corresponding knowledge point
reviewing an old knowledge point	The difficulty level of the corresponding knowledge point -1
visual task	2
non-essential knowledge point event	1

Here, we explain the coding rules in details:

1) Generally, when the instructional event is delivering a new knowledge point, the difficulty level of the event equals the difficulty level of the corresponding knowledge point.
2) When the instructional event is reviewing an old knowledge point, the event difficulty level equals the difficulty level of the corresponding knowledge point -1. The event difficulty level decreases because the students had encountered that knowledge point before. When the student reviews a knowledge point, he or she would feel less cognitive anxiety than the first time he or she encounters it.
3) A visual task is a task where the students are expected to read material such as a

question or computer code. The research in (Cho et al., 2000) indicates that in visual tasks mean blink frequency is affected by the position of gaze and not the level of task difficulty, so the event_dificulty_level for a visual task is a constant 2.

4) The non-essential knowledge point events, such as the tutor's self-introduction or when the tutor talked about a light-hearted topic. The event difficulty level for this segment was set at 1 because the students feel relaxed with this kind of content.

After coding each event segment, the average difficulty level for each minute was calculated, because the duration of each instructional event was not fixed, and could therefore be shorter or longer than one minute. The average event difficulty level for each minute was calculated on the basis of each event's proportion in that minute and its event difficulty level. For better comparison, the average event difficulty was normalised by using the maximum value of the average event difficulty level in each session as the divisor for that session.

3.2.3 Processing the data in the stimulated recall

The students' report in the stimulated recall was processed with the steps below:

1) To mark the emotional states. The emotional states of {happy, interest, flow} were marked with 0, the emotional states of {boredom, confusion, frustration} were marked with 1, and in few cases that the students reported with unknown were marked with 0.5. Here we classified {happy, interest, flow} into positive

emotional states and {boredom, confusion, frustration} into negative emotional states. These values are called emotion values.

2) To calculate the average emotion values for each minute on the basis of each record's proportion in that minute and its emotion values for each student.
3) To normalize the average emotion value by using the maximum value of the average emotion value for each student as the divisor.
4) To average the normalised emotion values of five students in each session, and this value is called AN emotion value.
5) To normalize the AN emotion value by using the maximum value of AN, and this value is called NAN value which varies between 0 to 1.

3.3 Results

After the data processing for the observation experiments, the results are summarized in sections 3.3.1 etc. Result 1 describes the students' movements in non-interactive environment and in interactive environment. Result 2 describes what kind of emotion the students feel in the interactive environment and the causes. Result 3 describes the tutor's interpretation of their teaching activities. Result 4 describes the relationship between the students' blink frequency, the event difficulty level and the emotional level.

3.3.1 Result 1

The number of body movements per minute shows no apparent correlation with the difficulty of the material presented. When the students were watching the non-interactive instructional video, they exhibited very little movement. The average number of movements per minute in session 1 was 1.23, and the number in session 2 was 1.56. This result indicates that it is not feasible to adopt a facial expression recognition technique or posture recognition technique to detect the learner's emotional state because the changes of external expressions and behavior are subtle and not large enough to be significant. The students were more active in the interactive environment than in the non-interactive environment. They exhibited more changes of facial expressions and body movements The average number of movements per minute in session 3 was 7.64, and the number in session 4 was 5.44.

Some students thought aloud when the tutor in the video asked questions in the non-interactive environment. This phenomenon may indicate that the students would prefer to interact with the tutor in the video.

3.3.2 Result 2

Here, the results from the students' stimulated recall are described:

From the stimulated recall of the students in the interaction environment, there were 266 original records in total obtained. The proportion that each emotional state occurred in the experiments is presented in Figure 3-1:

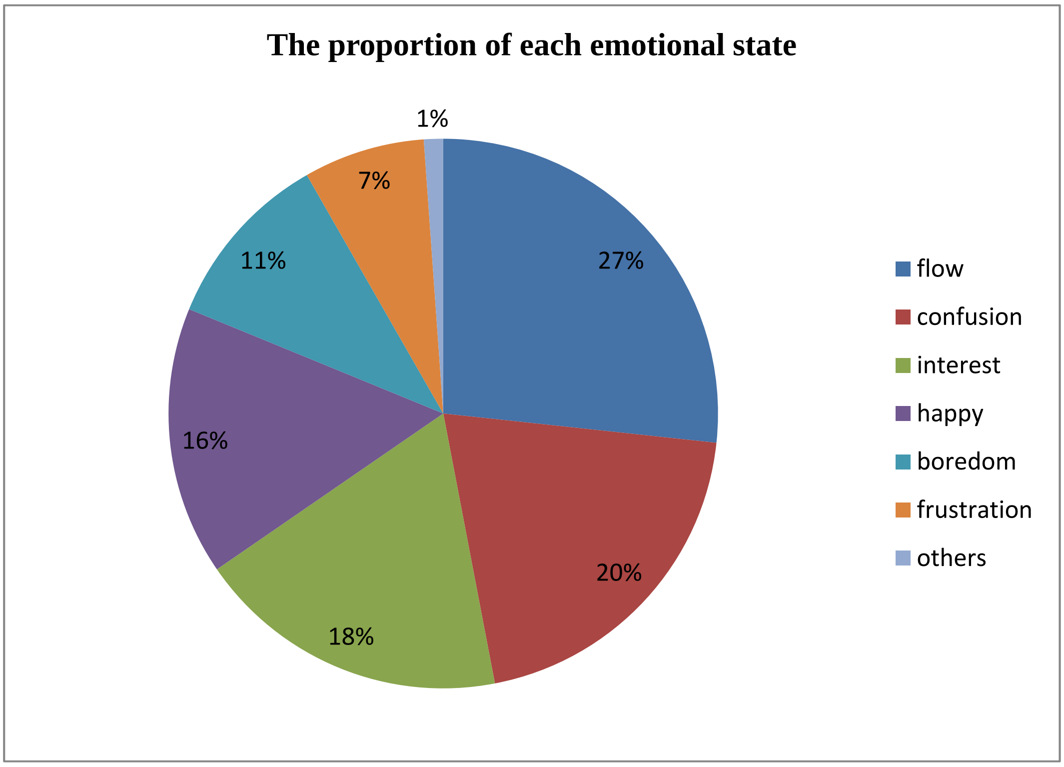

Figure 3-1 The proportion which each emotional states occupies

Although the students reported some emotional states not within the emotional state list provided, these formed a small proportion of the total reported. The emotional states in the emotion set we defined occupy 99%, so the emotion set is reasonable and feasible for use in the next phase of this research. The 1% emotional states not in the defined emotion set are one “surprise” and two “helplessness”. In the student’s report, the cause of “surprise” is that the tutor talked about the difficulty of exam and the student felt surprised for that high difficulty level. The causes of “helplessness” are that the stuff is too difficult to understand. The “helplessness” is close to “frustrated”, but the student listed it out independently, maybe because they feel the stuff is too difficult to understand.

3.3.3 Result 3

The students' descriptions about the causes of their emotional states were analyzed and the main causes for each emotional state were listed in Table 3-3 below:

Table 3-3 Students' interpretation about the possible causes of their emotions during learning

Emotional state	***Main possible causes***
Flow	• The students understood the knowledge point and kept pace with the tutor. • Thinking by themselves.
Interested	• Delivering new knowledge point • Tutor proposed questions about new knowledge point • Reviewing old knowledge point • Repeating old knowledge point that the student not understood yet • Using picture to explain knowledge point
Happy	• Student understood the knowledge point. • Student gave a correct answer. • The tutor was talking about a story.
Confused	• The student did not understand the knowledge point. • The student forgot the old knowledge point. • The student did not keep pace with the tutor.
Frustrated	• Student did not understand the knowledge point. • Student gave an incorrect answer.
Bored	• Student understood the knowledge point. • Reviewing old knowledge point.

Table 3-4 Teachers' interpretation about the causes of their activities during teaching

Causes		***Next tactics***
No special response from the students.		Delivering knowledge points as scheduled.
Tutor observed the student's emotional state was negative, such as confused or frustrated, during the lecture.		Pause and ask students related questions in order to know which knowledge point caused the negative emotional state.
		Review related knowledge points.
		Repeat the current knowledge point, present more examples.
		Delivering knowledge points as scheduled. (This is a part of the teaching plan in order to make the students focus on the next part.)
Question & Answer Segments	Student gave a correct answer.	Delivering knowledge points as scheduled.
	Student gave a partial correct answer.	Giving hint.
		Explain and complete the answer.
	Student had no answer.	Explain about the question further.
		Giving hint.
	Student gave an incorrect answer.	Explain about the question further.
		Giving hint.
		Repeat the current knowledge point, present more examples.
		Delivering knowledge points as scheduled. (This is a part of the teaching plan in order to make the students focus on the next part.)

The teachers' interpretations about the causes of their activities are summarized in Table 3-4. It can be seen from Table 3-4 that the explanation of the teachers' responses to the students can be classified into two types, one is driven by the students' emotional states, and the other is driven by the students' answers or cognitive states.

In order to further specify the relationship between the student's emotional state and the teacher's feedback tactics, the causes of the students' emotional state and the teachers' tactics are integrated to form Table 3-5.

Table 3-5 Extended tutor's response driven by emotional states

Emotional states	***Causes***	***Next tactics***
Flow	The students understood the knowledge point and kept pace with the tutor.	Delivering knowledge points as scheduled.
	Thinking or taking notes for the last knowledge point, did not keep pace with the tutor.	Pause and remind the student later.
Interested	Delivering new knowledge point Tutor proposed questions about new knowledge point Reviewing old knowledge point Repeating old knowledge point that the student not understood yet Using picture to explain knowledge point	Delivering knowledge points as scheduled.
Happy	Student understood the knowledge point.	Delivering knowledge points as scheduled.
	Student gave a correct answer.	The same with in Q&A.
Confused	The student did not understand the knowledge point.	Repeat the current knowledge point, give more examples, or communicate with the student.
	The student forgot the old knowledge point.	Jump to the old knowledge point, or communicate with the student.
	The student did not keep pace with the tutor.	Ask the student question to figure out which knowledge point should be jumped to.
Frustrated	Student did not understand the knowledge point.	Repeat the current knowledge point, give more examples.
	Student gave an incorrect answer.	The same with in Q&A.
Bored	Student understood the knowledge point.	Jump to the next knowledge point.
	Reviewing old knowledge point.	Jump over the review part, delivering the knowledge point directly.
	Student was tired.	Pause, and using light-hearted material to refresh the student.

These results are used in constructing the emotion analysis model and the feedback model in Chapter 4.

3.3.4 Result 4

Besides the results above, through the normalization process described in section 3.2, the relationship between the students' blink frequency, emotional level and the event difficulty level are described in the Figures below:

Figure 3-2-1 to Figure 3-2-4 show the normalised average event difficulty level per minute in solid line chart and the NAN blink frequency in dash line chart.

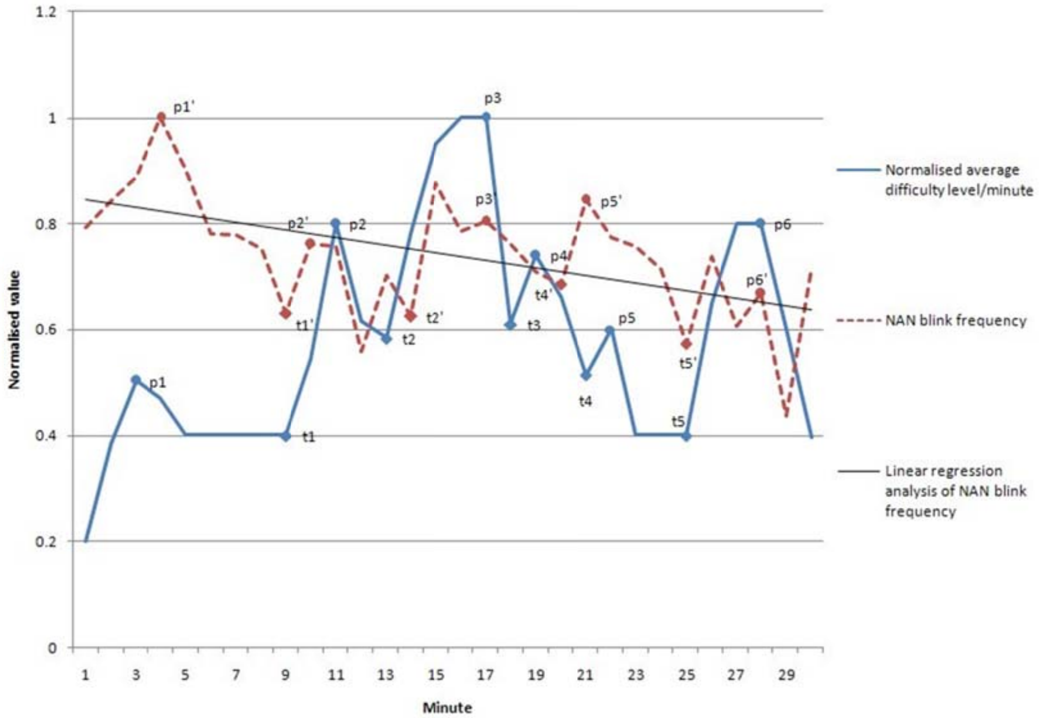

Figure 3-2-1 session 1

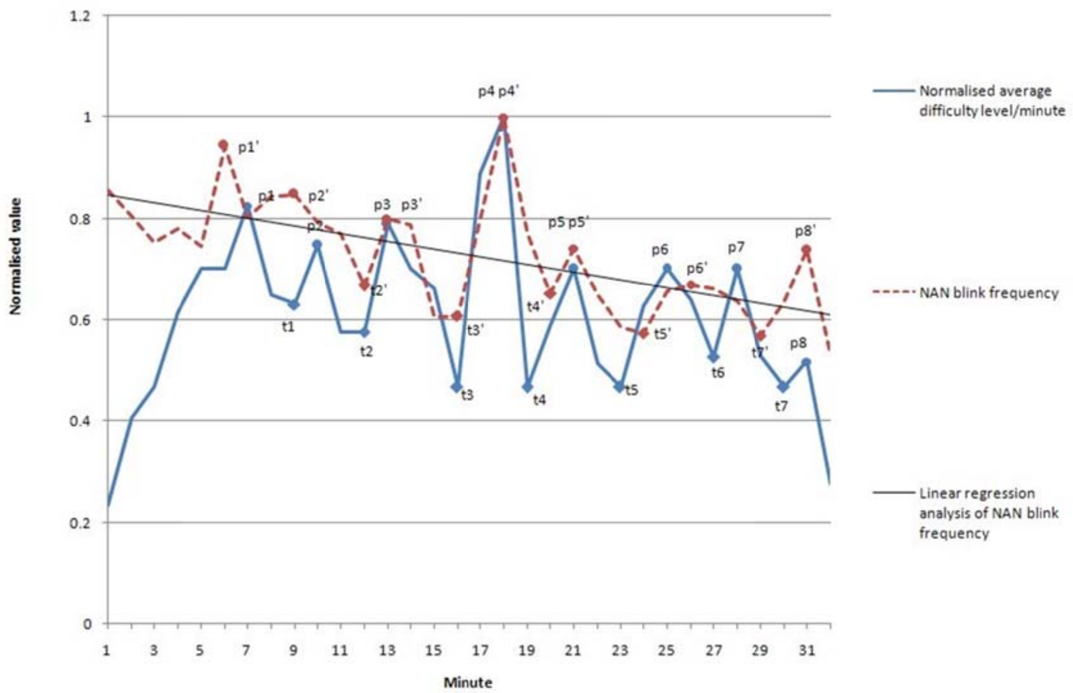

Figure 3-2-2 session 2

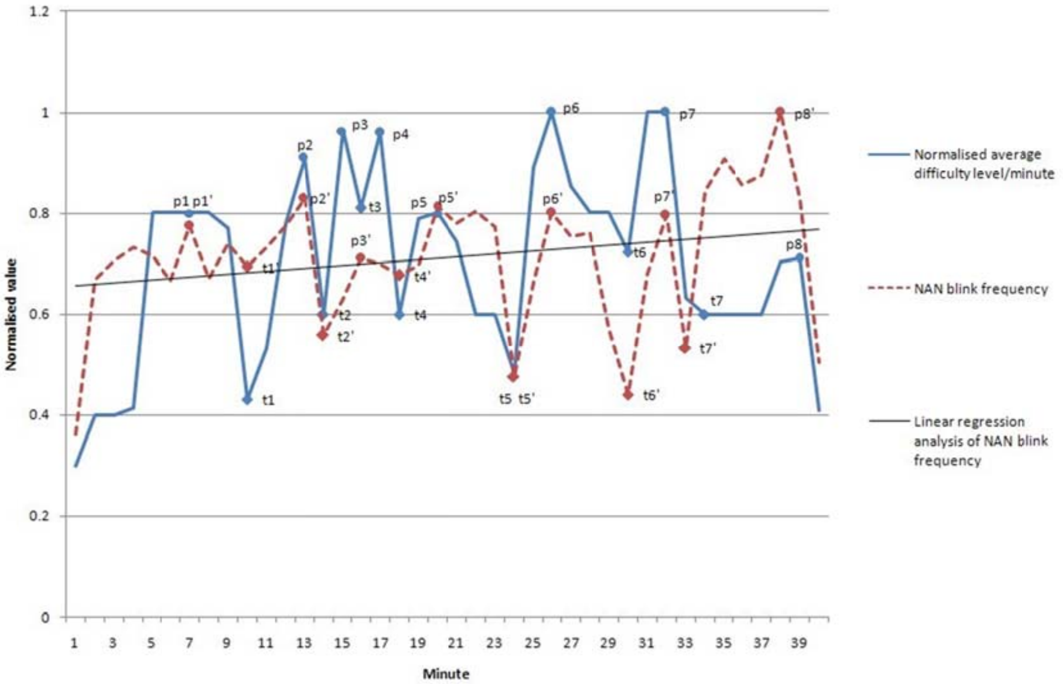

Figure 3-2-3 session 3

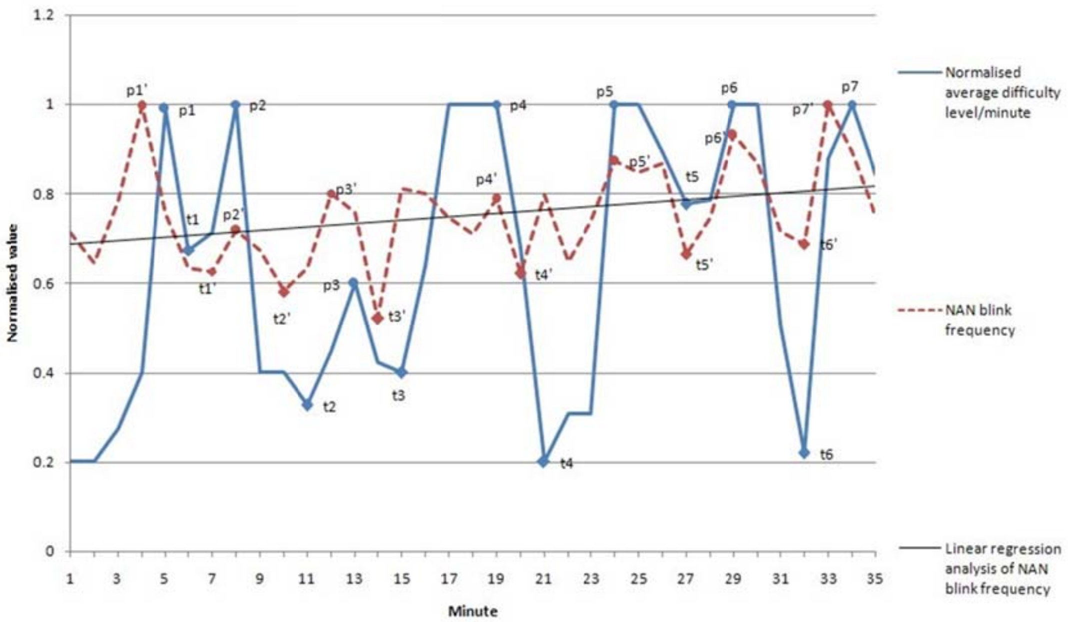

Figure 3-2-4 session 4

Figure 3-2 The normalised average event difficulty level per minute and the NAN blink frequency in each session

The peaks and troughs in the normalised average event difficulty level line are marked by p and t plus a number respectively, and the corresponding peaks and troughs in the NAN blink frequency line are marked with the same label plus a superscript "′".

From these figures, we can see that the two line charts have similar fluctuations in all the sessions. The number of the overlapped peaks and the overlapped bottoms in these figures were used to analyze the relationship between the blink frequency and the task difficulty level. In the four figures, we see that for almost every peak in the event difficulty chart, there is also a peak in the blink frequency chart. For example, in Figure 3-2-1, the peaks in the event difficulty chart appear at minute 3, 11, 17, 19, 22, 28, and around each peak, the peaks in the blink frequency appear at minute 4, 10, 17, N/A, 21, 28. One minute offset is permitted in the analysis because of the average process caused by uncertain event interval. In the four figures, from Figure 3-2-1 to Figure 3-2-4, there are 29 peaks in total in the event difficulty chart, and 26 peaks in the blink frequency chart overlap them, the overlap rate is 89.66%. The same situation applies to the troughs, and the overlap rate is 84%.

In the visual tasks, the students' blink frequency locates in the lower part. For example, in session 4, at the 23rd, 28th, and 31st minute, the students were undertaking visual tasks, they were reading the problems that the tutor showed on the slides.

From the analysis of Figure 3-2-1 to Figure 3-2-4, it could be infered that the blink frequency is correlated with the event difficulty level.

In order to investigate the relationship between blink frequency and emotion directly, the NAN blink frequency and NAN emotion level charts in session 3 and session 4 are produced in Figure 3-3-1 and 3-3-2 respectively.

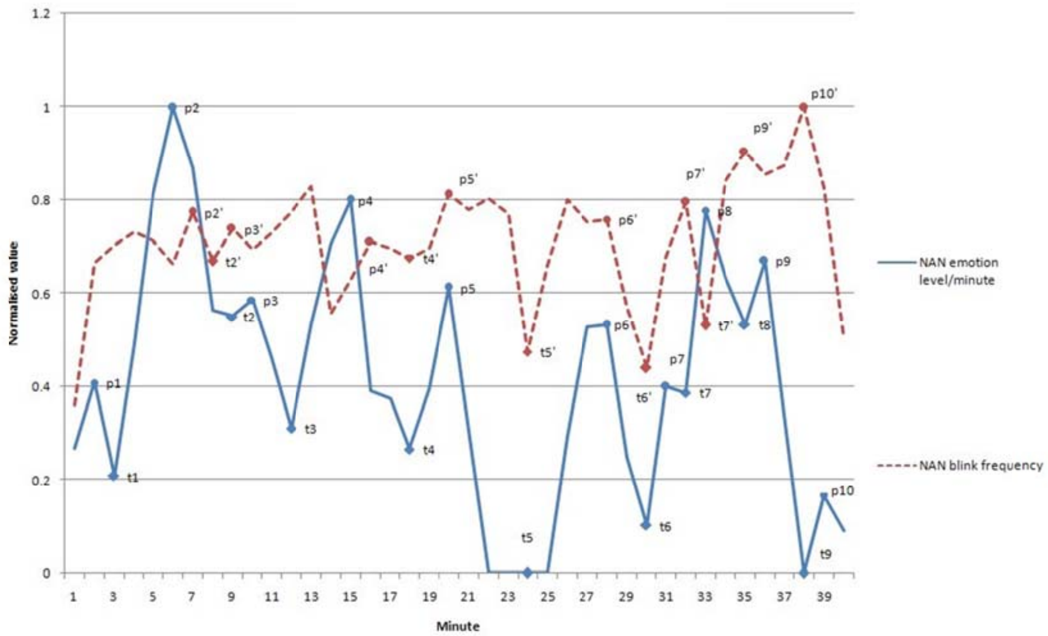

Figure 3-3-1 session 3

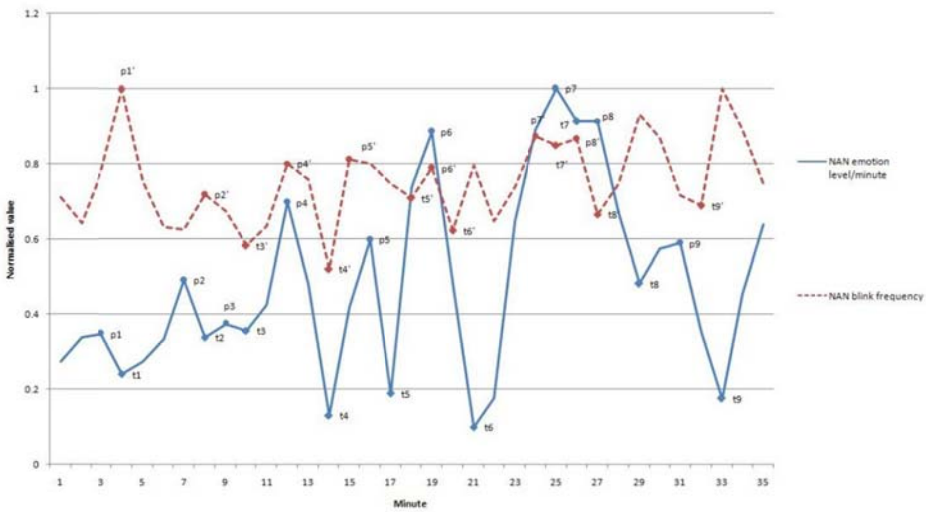

Figure 3-3-2 session 4

Figure 3-3 The NAN emotion level per minute and the NAN blink frequency

The peaks and troughs in the NAN emotion level line are marked by p and t plus a *number respectively, and the corresponding peaks and troughs in the NAN blink frequency line are marked with the same label plus a superscript "′".*

It can be seen from Figure 3-3 that the NAN emotion level line and the NAN blink frequency have the similar fluctuations obviously in partial region of the figures, such as from minute 18 to 32 in Figure 3-3-1, from minute 10 to 33 in Figure 3-3-2 and etc. The students marked their emotional states on the basis of their feelings but not in fixed interval. So in the average process, some "emotional level" was averaged in the neighbouring minutes. Therefore, one minute offset is also permitted in the analysis because of average process caused by uncertain intervals, when the student marked their emotional state. In the two figures, Figure 3-3-1 and Figure 3-3-2, there are 19 peaks in total in the event difficulty chart, and 15 peaks in the blink frequency chart overlap them, the overlap rate is 78.95%. The overlapped troughs are 12 out of 18, approximately 66.67%. The influence of the visual tasks was not counted in Figure 3-3. Blink frequency increases when negative emotions occurs, and blink frequency decreases when a student is in a visual task. When these two conditions appear at the same time, namely a student has negative emotions in a visual task, the emotion level reported by the student is high, but the blink frequency is still in lower level (Tanaka and Yamaoka, 1993). This is the main reason why the overlap rate is not as high as in the Figure 3-2.Through the observational four sessions with different conditions, we drew the conclusion that the blink frequencies in learning were associated with the learner's emotional state and were mainly affected by three factors, the difficulty level of the knowledge point, the task types, and the individual. This is also supported by

Tecce (1992), Tanaka & Yamaoka (1993), Drew (1951), Doughty and Naase (2006).

3.4 Discussion

3.4.1 Discussion about the necessity of interference for self-learning by watching video

Here, we discuss the linear regression analysis chart in Fig. 3-2-1 to Fig. 3-2-4. In our observations, the overall tendency of the blink curve in self-learning experiments decreased gradually for both two sessions. In contrast, the blink curves produced in both sessions of interactive learning with a human tutor did not show a declining tendency, but show an increasing tendency. In terms of the study results from Harrigan and O'Connell (1996) and Pacheco-Unguetti AP *et al* (2010), it is known that more eye blinks were observed during periods of high anxiety as opposed to periods of low anxiety, and there is a clear relationship between anxiety levels and attention. Therefore, it is deduced that the blink frequency curve reflects the attention level of the learner. If the hypothesis is correct, the decreased tendency in blink could be explained as a downward trend in attention due to self-learning, whilst the increase in blink frequency could be explained as a upward trend in attention levels due to the tutor’s intervention. So, it is necessary to intervene when students are in self-learning through watching instructional video in order to ensure that attention levels do not continue to decrease.

3.4.2 Discussion about how to use blink frequency in affective learning

On the basis of the experimental results and literature mentioned above, blink frequency could indicate the student's emotion, it could be used to estimate which type of emotional states, negative or positive, the students are in, by introducing an individual threshold value as shown in Figure 3-4. The knowledge points where the learner shows a high blink frequency over the threshold line could be marked and at the end of the instructional video, the affective learning system could present the learner with more related learning material and exercises concerning the marked points. The greatest challenge existing in such applications is individual difference. We therefore need an approach to adjust the thresholds in terms of different individuals. For example, we could arrange for a student to watch some benchmark videos to obtain their average blink frequency. In addition, we would need to update the student's individual threshold line when the student wears or takes off contact lenses because the wearing of contact lenses causes an increase in blink frequencies (Tada and Iwasaki, 1984).

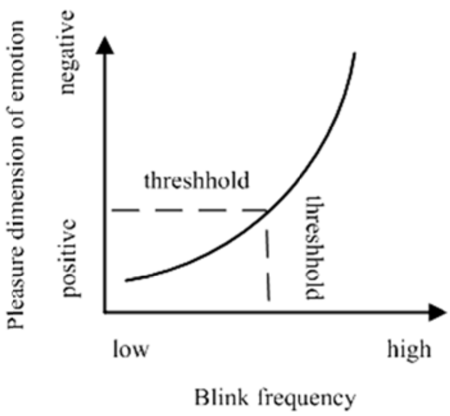

Figure 3-4 The relationship between the blink frequency and the pleasure dimension of emotion

Alternatively, the estimated results could be used to adjust the tactics used in the following teaching session for an individual. We need to do more analysis of the knowledge points and the learner's performance history in order to verify whether the learner is in anxiety or fatigue, because anxiety and fatigue both cause increased blink frequency. If the knowledge point is easy and the learner is known to be capable of coping with the material, we may deduce the learner feels fatigue (arising from boredom). The affective learning system could pause and let the student choose to take a break by listening to music or by watching a humorous video. But if the knowledge point is difficult, the learner would probably be anxious. The system could slow down the teaching pace and show more examples.

In the implementation of the system, the blink frequency can be calculated in real-time by a program connected to a web camera. We have found some blink recognition algorithms, such as in (Chau and Betke, 2005, Wu and Trivedi, 2007).

3.5 Summary

This chapter introduced the methodology, experimental design, data processing and results of the video study. The methodology adopted in this video study is called "Quick and Dirty Ethnography", which has a trade-off between the efficiency and the completeness. In the observation study, a total of 15 students, 2 tutors, 4 sessions were used to see how emotion works in non-interactive environments and interactive environments. "Stimulated recall" was carried out by the students and tutors in the interactive environment in order to collect the cause of the student's emotional states and how the tutors respond to the student's emotional states. In the data processing, blink frequency, body movements, instructional videos and reports in the stimulated recall were analysed. The conclusions in the background study are summarized below:

- The number of body movements per minute shows no apparent correlation with the difficulty of the material presented.
- The emotion set {boredom, frustration, confusion, flow, happiness, interest} are examined by the students, and the results indicated that the emotion set is reasonable and feasible for the research.
- The students' descriptions about their emotional states and the causes of their emotional states, and teachers' interpretation about the causes of their activities during teaching were collected and summarized in Table 3-3 to 3-5.
- Through the four observational sessions with different conditions, we drew the conclusion that the blink frequencies in learning were associated with the

learner's emotional state and were mainly affected by three factors, the difficulty level of the knowledge point, the task types, and the individual.

- In our observations, the overall tendency of the blink curve in self-learning experiments decreased gradually in both sessions. In contrast, the blink curves produced in both sessions of interactive learning with a human tutor did not show a declining tendency, but show an increasing tendency. So, it is necessary to intervene when students are engaged in self-learning via instructional video in order to ensure that attention levels do not continue to decrease.

Chapter 4

Emotion analysis model and feedback model

4.1 Introduction

Experienced classroom teachers know that if they are to be successful they must react to the moods of the pupils in their classes. Traditional e-learning delivery mechanisms lack an ability to adapt to the emotional state of the learners. As the results in Chapter 3 show, in taught sessions the students' interest is kept alive whereas in straight video presentations the students' interest steadily declines. An essential prerequisite for e-learning systems that can modify their behavior with respect to the emotional state of a learner (affective learning systems) is a means to detect an emotional state. Ideally, such a mechanism will be relatively cheap, non-intrusive, accurate and will only make use of standard computer equipment.

Research into affect recognition has made substantial progress in recent years. Emotional states can be recognized through facial recognition (Korb et al., 2008, Whitehill et al., 2008, Linn, 2015), voice recognition (Truong et al., 2007, Laukka et al., 2011, Batliner et al., 2011), biological signal detection (Blanchard et al., 2007, Korb et al., 2008, Zhang and Lee, 2010), posture analysis (Dragon et al., 2008, D'Mello and Graesser, 2009), text based analysis (Quan and Ren, 2010, Neviarouskaya et al., 2010); appraisal by the learning context (Moridis and

Economides, 2009, Jaques and Vicari, 2007) and qualitative methods such as think aloud, and interviews (Chaffar and Frasson, 2006, Schutte et al., 1998, D'Mello et al., 2006). Qualitative methods obtain the emotional states from the learners' subjective reports, and other methods identify the emotional states by extracting patterns from the learner's external expressions, behavior or internal biological signals.

Some of these techniques have their limitations when applied in a learning environment. Qualitative methods, for example questionnaires, are easy to set up, but are intrusive to the learner's learning process, so they are not suitable for real-time emotion detection. Internal biological signals can be detected by professional and sophisticated biofeedback devices that have high costs and are intrusive to the learners, such as the electroencephalogram (EEG) (Hu et al., 2011), and the Galvactivator skin conductivity sensor (Picard et al., 2004). There are, however, some non-intrusive devices which can be used to measure internal signals, e.g. pressure mouse, but they are not generally used by the average computer user.

Observing external expressions and behavior is an intuitive and effective way to recognize the learner's emotional state during classroom teaching, it has a low cost and is less intrusive when incorporated into an affective system. External expression recognition techniques normally adopt less intrusive devices, such as web-cameras, microphones and human-computer interactions. These devices are low cost and often provided by the learners, and therefore the only additional analytical requirements are the specialised algorithms and software to support them.

Using low cost universally available facilities to acquire the learner's emotional state is a way to realize affective learning systems. Among the methods for detecting external expressions and behavior, facial recognition techniques have attracted considerable attention. Facial recognition is the analysis of facial features, by comparing them with a facial database or the Facial Action Coding System (Ekman and Friesen, 1978a), to deduce the user's emotional state. In facial recognition, eye movements, including squeezing or raising eyebrows, opening or closing eyelids, are an important part of the emotional cues. Indeed, eyes are a very active organ on the face which indicate a subject's attention, fatigue, and emotion. Most research is, however, focused on how to apply the static characteristics of eye movements rather than the dynamic ones. The dynamic characteristics of eye movement include blink frequency, the interval between two blinks, the duration of time of each blink, eyeball motion, etc. Some research has focused on using dynamic features of eye movement in the detection of mental state (Bittner et al., 2001, Miteshkumar et al., 2010, D'Mello et al., 2012), but less literature exists about emotion detection that uses blink frequency as the main index in affective learning.

Using eye blink as an index to recognize the learner's emotional states has advantages over other methods:

- Measuring blink frequency is a non-intrusive way to identify the learner's emotional states during their learning process, which could avoid the disturbance created by other intrusive techniques, such as EEG measurement, or questionnaires.
- The input information, the blink frequency and duration, is continuous, and it is

easier to collect than data on other facial expressions which only emerge when the learner is in relatively intense emotional states.

- Blink frequency measurement can be undertaken using a simple web camera. Blink recognition algorithms making use of this technique are described in (Chau and Betke, 2005, Wu and Trivedi, 2007). This device is readily available and much cheaper than the Bio-Feedback facilities required in order to measure EEG and heart rates.

On the basis of the study described in chapter 3, we know that an analysis of eye blink frequency is a feasible approach for the detection of emotion. The new affective learning system could, therefore, adapt its instruction based on an evaluation of the students' emotional state which will be made by measuring their blink rates.

In addition, the video-recorded lecture is a primary feature of most online learning platforms and many educational institutes use video lectures to improve the effectiveness of teaching in and out of classrooms and to support distance-learning students, such as Coursera, Khan Academy, and TED. (Breslow et al., 2013, Brecht and Ogilby, 2008, Chen and Wu, 2015). A new affective learning system can therefore designed for e-learning by using video lectures as the primary instructional material.

This chapter will introduce the emotional models in the affective learning system, emotion analysis model and emotion feedback model. The modeling technique, the construction process of these models and the case studies of both models will be presented.

4.2 Related research work of emotion models

Here, the design of the emotion models of affective learning systems are reviewed. Some affective learning systems provide feedback to the learner on the basis of the emotional state directly without an independent emotion analysis model, such as (Lahart et al., 2007, Robison et al., 2009a, Woolf et al., 2007, Woolf et al., 2009). Lahart, et al (2007) determined the feedback tactic on the basis of the emotional state and learning phase. For example, IF(emotional state = sad AND phase = beginning) THEN tutoring tactic = Motivational Game. In (Robison et al., 2009a), the agent directed students in a negative emotional state towards information that would help them complete the goal, because the cause of the emotion is difficult to establish. In (Woolf et al., 2009), the Wayang intelligent tutor used a variety of heuristic strategies, such as mirroring student actions, to respond to student affect. Machine learning optimization algorithms have been used in the Wayang intelligent tutor to search for policies for individual students in different affective and cognitive states, with the goal of achieving high learning and positive attitudes towards the subject, compared to pre-defined heuristic policies. These systems did not analyse the causes of the emotional states further, but instead responded to the learner on the basis of the emotional state and learning context directly. This makes the understanding of the causes of the emotional state unclear. In addition, the learning environment in these systems is instructional games, or intelligent instructional systems, none of these are present in a video learning environment.

Some research took into account an analysis of the causes of the emotional states.

Boulay (2011) distinguished two kinds of causes of a transition towards a negative motivational state, values-based and expectancies-based. Some other systems, such as (Hernández and Sucar, 2007, Conati and Maclaren, 2005, Jaques et al., 2004), adopt a subset of the emotion states developed by OCC theory (Ortony et al., 1990) , or variations on this, to reason about the causality in learning situations. The OCC model is a psychological model of emotions that provides a clear and convincing structure of the eliciting conditions of emotions and the variables that affect their intensities and it is popular among computer scientists that are building systems that reason about emotions or incorporate emotions in artificial characters (Steunebrink et al., 2009). These systems have active interaction with the users by the operations in the instructional game or the results of the execution of an exercise, and the learning environment is different to the video based learning environment. In addition, these systems lack consideration of the teaching procedure itself and the content of the material, which means that the learners' cognitive states during learning have not been analyzed comprehensively.

So, in our system, in order to determine the causes of the emotional state and produce more appropriate feedback in a video learning environment, the emotion analysis model and the emotion feedback model are designed independently.

4.3 Emotional models in the affective learning system

On the basis of the above analysis of the related research work, three features are determined in the new affective learning system:

- The new affective learning system can adapt its instruction based on an evaluation of the students' emotional state which will be made by measuring their blink rates.
- The new affective learning system is designed for e-learning by using video lectures as the primary instructional material.
- In the new affective learning system, the emotion analysis model and the emotion feedback model are designed independently.

The emotional models in the affective system are presented in Figure 4-1. There are two emotional models, one is the emotion analysis model which is used to analyse the specific emotional state and the cognitive state that causes the emotional state, and the other is the feedback model which is used to select the appropriate feedback tactics for the learner.

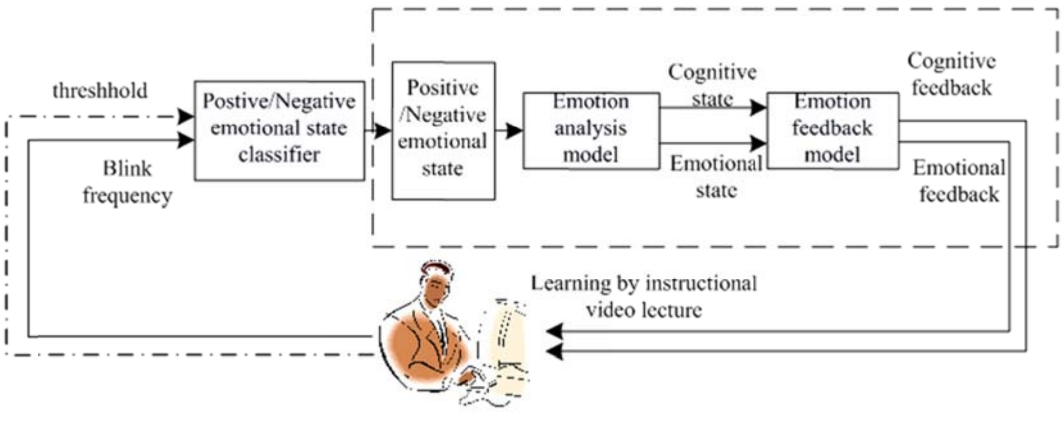

Figure 4-1 The emotion models in the affective learning system

By introducing an individual threshold value discussed in Chapter 3.4.2, it is possible to estimate which type of emotional states, negative or positive, the students are in. How to determine the threshold line of blink frequency will not be discussed further in this paper. Besides the blink frequency, the positive or negative emotional state could be detected through voice or facial expression (Lee et al., 2001, Zakharov et al., 2008). Here, we assume that a learner's emotional state can be classified into positive and negative states through blink frequency, or other cues. This chapter will discuss how to determine a student's positive or negative emotional state and how to select appropriate feedback when the emotional state is identified.

The emotion analysis model and feedback model will be introduced in detail in the following sections, including the related techniques and how to construct these models.

4.4 The Emotion analysis model

The emotion analysis model，also called the emotion cause analysis model, sets out to determine not only the emotional state but also the cause of the emotional state. It is different from the emotional recognition model which is used to detect or appraise which emotional state the learner is in. The input to an emotional recognition model is facial expression, bio-signal, learning contextual information, etc., and the output is the emotional state. However for the emotion analysis model, the input is the learning contextual information, the learner's information, etc., and the output is the emotional state and the cause of the emotional state in cognitive aspects. Hereafter, only the cognitive states are taken into account as the cause of the emotional state, because this aspect is the main factor that affects the learner's emotional state during the learning process.

4.4.1 Review of modeling techniques in the Emotion analysis model

With respect to the problem of how to understand learners' emotional states, three common modeling techniques are introduced, respectively are HMM (Hidden Markov Model), Fuzzy Logic, and Bayesian network. The Hidden Markov Model (Baum and Baum, 1972) is a tool for modeling systems with sequential observable outcomes when the states producing the outcomes cannot be directly observed (i.e. they are hidden). The research work, such as (Grafsgaard et al., 2012, D'Mello and Graesser, 2010, Grafsgaard et al., 2011), utilize a HMM technique to model state transition in an instructional process. Fuzzy Modeling is a modeling technique based on Fuzzy Logic (Zadeh, 1965). Fuzzy logic deals with reasoning that is approximate rather than fixed and exact. The research work, such as (Almohammadi and Hagras, 2013, Crockett et al., 2011),uses Fuzzy logic as a modeling tool. HMM and Fuzzy Logic are both suitable for modeling the emotion problem with uncertainty, however, they cannot represent a causal relationship which is needed in an emotion analysis model. As mentioned previously, the emotion analysis model is designed to determine the cause of the emotional state, therefore, the causal relationship between the cognitive state and emotional state needs to be represented. A Bayesian Network (BN) is a directed acyclic graph is which each node is annotated with quantitative probability information it is sometimes also called a Bayesian belief network (BBN), a Bayesian model or probabilistic directed acyclic graphical model (Russell et al., 1995). A Bayesian belief network, as a modeling tool, is for dealing problems with uncertainty and complexity and can represent the causal relationship. Amongst the researchers adopting BN as a modeling tool are (Leontidis et al., 2009, Arroyo and Woolf, 2005, Ghazali et al., 2014, Sabourin et al., 2011a). On the basis of the analysis above, BBN is a straightforward and sufficient modeling tool for establishing the casual relationship between the cognitive state and emotional state when interpreting the emotional states.

4.4.2 Introduction of Bayesian networks

A Bayesian network (Pearl, 1985) is a directed acyclic graph in which each node is annotated with quantitative probability information. The graph is a visualization of the conditional independence relationships between different variables. The other part of a Bayesian network is the conditional probability tables (CPTs) which define the conditional probabilities for each node, given its parents (de Jongh, 2005). A Bayesian network represents a joint probability distribution in the following way:

$$P(x_1,\ldots,x_n) = \prod_{i=1}^{n} P(x_i \mid parents(X_i)) \quad \text{(Equation 4-1)}$$

Equation 4-1 joint probability representation

Bayesian networks have several advantages:

1) Since the dependencies of all variables are encoded in a Bayesian network, missing data entries can be easily handled.
2) A Bayesian network has both causal and probabilistic semantics, so it is an ideal tool to represent prior knowledge and data
3) The causal and uncertainty representation structure in a Bayesian network

provides powerful capabilities to handle complex situations in practical systems.

4) Given the causal nature of a Bayesian network, it can be used to gain an understanding of a problem domain and to predict the consequences of intervention.

Modeling emotion is an uncertain and complex problem because the emotional state is a state of mind that cannot be read directly. The Bayesian probabilistic model, however, is capable of dealing with uncertainty and complexity. In addition, a Bayesian network represents the casual relationship and the prior knowledge in graphical network form, so, this is good for understanding a problem domain as well as forecasting the consequences. Considering the complexity in teaching and learning process, the uncertainty of emotion during learning, and the analysis of the cause of the emotional state, a Bayesian network, which has causal and uncertainty representation ability, is an ideal tool to model the emotion problem in learning.

Bayesian networks have been extensively adopted in affective learning research. Sabourin, Mott et al.(2013) used Bayesian modeling techniques incorporating both empirical and theoretical knowledge to improve the classification accuracy of student self-regulated learning skills. Sabourin, Mott et al.(2011b) used Bayesian networks for predicting student affect with a structure informed by a theoretical model of learning emotions. Bayesian networks have been used to model the cognitive appraisal process.

4.4.3 Emotion representation model

As mentioned in chapter 2, there are two main types of emotional state representation model, categorized emotion representation and dimensional emotion representation. The presentation of the emotional state with the dimension of valence (positive or negative), arousal, dominant, is called a dimensional model, and representation of the emotional states by specific classification, such as happy, confusion, is called a categorized model. The representation model produced by analyzing blink frequency is a kind of one dimensional model which adopts the dimension of valence. It is simpler to classify emotional states by using a one dimensional model than a classification model because the dimensional model requires less information. The dimensional model is not rich enough to allow a full understanding of an emotional state in a learning environment, so we need to know more information about a positive or negative state, especially the related cognitive state with respect to an emotional state. The classification model embraces cognitive information about an emotional state, for example, if a learner feels confused, this means the learner's cognitive state is blocked.

Here we define the dimensional model and the classification model in the emotional analysis mode.

The emotional one dimensional model: {positive, negative}.

The emotional classification model: {happy, interested, flow, bored, confused, frustrated}.

The positive state set P={happiness, interest, flow}, and the negative state set

N={confusion, frustration, boredom}.

Happiness, interest, confusion, frustration, and bored in this context retain their everyday conventional meanings. Flow represents the feeling of complete and energized focus in an activity, with a high level of enjoyment and fulfillment (Debold, 2002). In the flow zone, the abilities of the student match the difficulty level of the learning material, for example, they can understand the materials delivered by the tutor well and they can give the correct answer to a problem.

A specific emotional state in the classification model could be transferred into a state in the dimensional model (Cowie et al., 1999), but conversely, an emotional state in the dimensional model cannot be transferred into a state in the classification model without additional information. For example, confusion is definitely a negative emotional state, but a negative emotional state could be confusion or frustration. Within a learning environment, however, the learning contextual information could be helpful in the transfer process. For example, if a negative state appears in the step of stimulating recall of prior learning, and the student had learned the prior knowledge point very well, then there is a high probability that the emotional state of the learner is boredom because the learner has understood that knowledge point already.

4.4.4 Emotional state and corresponding cognitive state

In a learning environment, we assume the learner's emotional states are all caused by the changes of the cognitive states. A learning process is divided into nine instructional steps in term of Gagne's theory(Gagne, 1965). Each instructional step is related to corresponding cognitive states. The cognitive state set C = {Receiving, Anticipating, Retrieving, Perceiving, Encoding, Responding, Reinforcing, Generalising}. We list the possible emotional state, cognitive state and the corresponding cause in each instructional step. The tables below are produced on the basis of the video study and the student's stimulated recall report which were summarized in Table 3-3, and the tutors' teaching experience which was used as supplementary support. In tables from Table 4-1 to Table 4-9, where the places with (*) is supplemented on the basis of tutors' teaching experience because these situations were not mentioned in the student's report (such as "bored" caused by "failed retrieval") or the instructional step did not appear in the instructional process (such as "enhancing retention and transfer").

The instructional steps are as follows:

1. Gaining attention - Helps students focus on relevant portions of the learning task. (reception)

Table 4-1 The mapping relationships between the emotional states and cognitive states in the step of gaining attention

Possible emotional states		**Cognitive states**
Positive emotional states	Interested, Flow, Happy	Successful reception.
Negative emotional states	Bored	Failed reception.

2. Informing learner of lesson objective(s) - Tells students what they are about to learn. (expectancy)

Table 4-2 The mapping relationships between the emotional states and cognitive states in the step of informing learner of lesson objective(s)

Possible emotional states		**Cognitive states**
Positive emotional states	Interested, Flow, Happy	Anticipating.
Negative emotional states	Bored	Non-expecting, students have learned the current knowledge point.
	Confused	Non-expecting, students cannot understand the learning content.

3. Stimulating recall of prior learning - Help students retrieve memories that are necessary or helpful in achieving new objectives (retrieval)

Table 4-3 The mapping relationships between the emotional states and cognitive states in the step of stimulating recall of prior learning

Possible emotional states		**Cognitive states**
Positive emotional states	Interest, Happy, Flow	Successful retrieval. Students learned the reviewed knowledge well and would like to review it.
Negative emotional states	Confused, Frustrated	Failed retrieval. Students did not master the reviewed knowledge well.
	Bored	Successful retrieval. Students learned the reviewed knowledge well and would not like to review it.
		Failed retrieval. Students did not master the reviewed knowledge well. (*)

4. Presenting stimuli with distinctive features - Expose students to information that they will be learning (selective perception)

Table 4-4 The mapping relationships between the emotional states and cognitive states in the step of presenting stimuli with distinctive features

Possible emotional states		**Cognitive states**
Positive emotional states	Happy, Flow, Interested	Successful perception.
Negative emotional states	Confused, Frustrated	Failed perception. Students do not understand current knowledge well.
		Failed perception. Students do not master the prerequisite knowledge point well.
	Bored	Failed perception. Students do not understand current knowledge well. (*)
		Successful perception. Students understand current knowledge well.

5. Providing learning guidance - Provide students with clues to help them understand and remember what they are to learn (semantic encoding)

Table 4-5 The mapping relationships between the emotional states and cognitive states in the step of providing learning guidance

Possible emotional states		**Cognitive states**
Positive emotional states	Interested, Happy, Flow	Successful encoding.
Negative emotional states	Confused, Frustrated	Failed encoding. Students do not understand current example well.
	Bored	Failed encoding. Students do not understand current example well.(*)
		Successful encoding. It is too easy for the student.

6. Eliciting performance - Gives students an opportunity to demonstrate that they have learned the new information to this point and are ready to proceed to the next part of the lesson (responding)

Table 4-6 The mapping relationships between the emotional states and cognitive states in the step of eliciting performance

Possible emotional states		**Cognitive states**
Positive emotional states	Interested, Happy, Flow(*)	Confident for responding. The students are confident to solve the problem.
Negative emotional states	Confused(*) Frustrated	Failed for responding. The students do not know how to solve the problem.

7. Providing feedback - Give students information about the adequacy of their responses in the "elicit performance" event (reinforcement)

Table 4-7 The mapping relationships between the emotional states and cognitive states in the step of providing feedback

Possible emotional states		**Cognitive states**
Positive emotional states	Happy	Student gave a correct answer.
Negative emotional states	Confused(*), Frustrated	Student gives a partial correct answer.
		Student gives an incorrect answer.
	Confused	Students do not know how to solve the problem. No answer.

8. Assessing performance -Assess whether the students have achieved the objectives of the session or unit (retrieval)

Table 4-8 The mapping relationships between the emotional states and cognitive states in the step of assessing performance

Possible emotional states		**Cognitive states**
Positive emotional states	Interested(*), Happy, Flow	Successful retrieval. Students learned the prior knowledge well and would like to review it.
Negative emotional states	Confused Frustrated	Failed retrieval. Students did not master the knowledge well.
	Bored	Successful retrieval. Students learned the prior knowledge well and would not like to review it.
		Failed retrieval. Students did not master the knowledge well.

9. Enhancing retention and transfer -Allow students to review and extend new so that it is available for subsequent application (generalization)

Table 4-9 The mapping relationships between the emotional states and cognitive states in the step of enhancing retention and transfer

Possible emotional states		**Cognitive states**
Positive emotional states(*)	Interested, Happy, Flow	Successful generalization. The students are confident they can solve the problem. (*)
Negative emotional states(*)	Confused Frustrated	Failed generalization. The students do not know how to solve the problem. (*)

On the basis of the tables from Table 4-1 to Table 4-9, it can be seen that the cognitive state that causes the positive emotional state is unique, while the cognitive state that causes the negative emotional state could be different. The causes of the negative emotional states are complicated, for example, in the step of stimulating recall of prior learning (Table 4-3), the cause of the negative emotional state could be “failed retrieval” or “successful retrieval”, which should be related to completely different feedback tactics. Therefore, the negative emotional states are the emphasis of analysis and response, especially for the state of “boredom”, that can only be accurately understood with reference to the cognitive state. Next, a Bayesian belief network model will be introduced to model the learner’s emotion and reason the learner’s cognitive and emotional state.

4.4.5 Using a Bayesian belief network to model the learner's emotion

From the tables above, on the one hand, we can see that the same emotional state could be caused by a number of different reasons, for example, in the step of "Stimulating recall of prior learning", boredom could be caused by "successful retrieval" or "failed retrieval". Only when the cause is certain, can the appropriate feedback be produced. On the other hand, the same cognitive state could cause a different emotional state, for example, in the same step, when students fail to retrieve, they could be in a different emotional state, such as confusion, frustration or boredom. In this situation, we could provide the same cognitive feedback to help students learn the related material further, but as to the emotional feedback, we should treat these cases differently. The prior problem will be dealt with in the cause analysis model and the latter problem will be dealt with in the emotion feedback model.

Since the cognitive states that relate to positive emotional state are consistent in each instructional step, we only focus on the analysis of the negative emotional states. Mathematically, the cause analysis problem may be viewed as a problem integrated with diagnosis. This cause analysis model is constructed by a Bayesian belief network. The top layer presents the learning contextual information, the middle layer represents the cognitive state, and the bottom layer is the specific negative emotional state. The information in the top layer could be obtained from the learner's profile and video clip information. In the middle layer, the nodes represent a learner's cognitive state which is related to a certain instructional step in terms of Gagne's theory (Gagne, 1965). For example, reception is a cognitive state related to the instructional step of "Gaining attention", if the current video clip has the objective of "Gaining attention", we can infer that other cognitive states are "NA" (not applicable) due to the independence between these cognitive states. Each state in the nodes and a sample of input and output nodes are shown in Figure 4-2. The emotion analysis model and feedback model are developed by a modeling tool called HUGIN software[2] which is based on complex statistical models known as Bayesian Networks and influence diagrams.

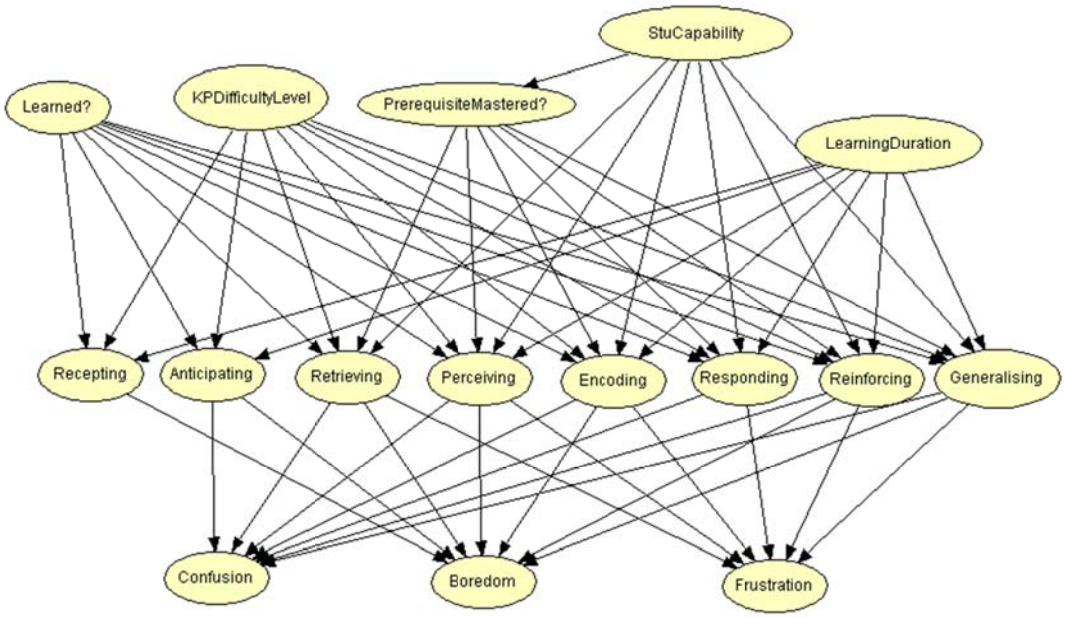

Figure4-2 The Bayesian belief network structure for the negative emotional state

The simplified representation for the BBN in Figure4-3 is as Figure4-4:

[2] http://www.hugin.com/

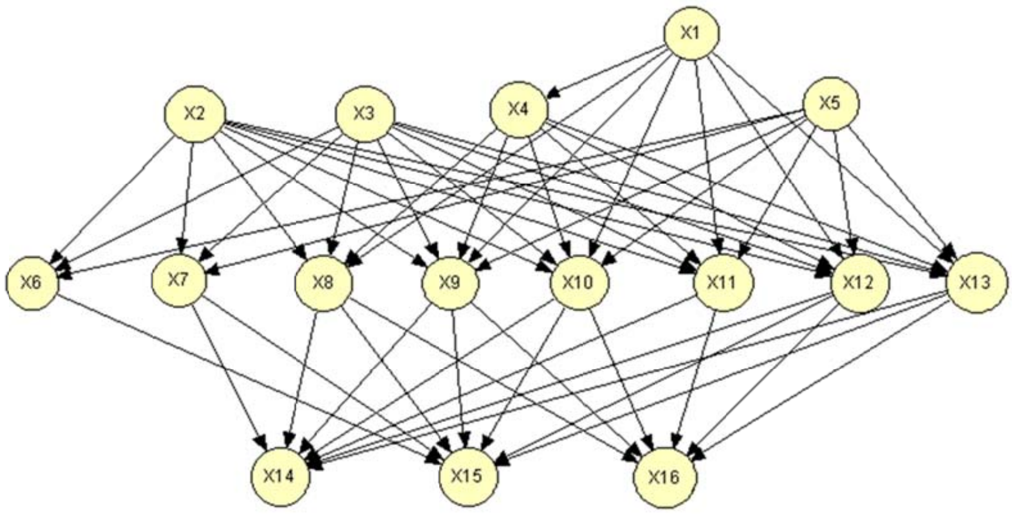

Figure4-3 The simplified representation for the BBN in Figure4-2

The joint probability of the Bayesian network in Figure 4-3 is:

$$P(x_1,...x_{16}) = P(x_{14} \mid x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}) \cdot P(x_{15} \mid x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14}) \cdot$$
$$P(x_{16} \mid x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}) \cdot P(x_6 \| x_2, x_3, x_4) \cdots P(x_4 \mid x_1)$$

Given a group of input (x1, x2, x3, x4, x5, x6, x7, x8, x9, x10, x11, x12, x13), (x1, x2, x3, x4, x5) is about the learning context and (x6, x7, x8, x9, x10, x11, x12, x13) is about the instructional step. Node x_j, one of (x6, x7, x8, x9, x10, x11, x12, x13), is absent on the basis of the current instructional step. The probability of each negative emotional state could be calculated using the BBN, and the node X that has the maximum probability to the state of "yes" could be selected using Equation (4-2).

$$X = \arg\max_{i=14,15,16} P(x_i | x_1, x_2 .... x_{13})$$ (Equation 4-2)

The learner's cognitive state is "successful" or "failed" could be inferred by equation (4-3), the state that has higher probability p is the learner's cognitive state.

$$p = m\mathrm{ax}(p(x_j = successful \mid x_1, x_2 .... x_{13}), p(x_j = failed \mid x_1, x_2 .... x_{13}))$$ (Equation 4-3)

Inference in Bayesian networks is performed by the Junction Tree algorithm (Lauritzen and Spiegelhalter, 1988).The conditional probability table is determined by the data in the video study and Expectation Maximization(EM) parameter learning algorithm (Lauritzen, 1995). The cases set for EM learning is obtained through processing the original cases in the video study. There are 266 original cases in the video study (Section 3) in total, including 162 cases about positive emotional states, 101 cases about negative emotional states and 3 unspecified cases. The cases about negative emotional state which are over 1 minute are divided into cases equaling or no longer than 1 minute. The case set produced in this way has 173 cases with a more reasonable distribution and the value of "learning duration" is more reasonable. This case set with 173 cases is used for parameter learning and to evaluate the emotion analysis model, and the evaluation process will be addressed in section 5.1.

Below are two examples of inference by the BBN:

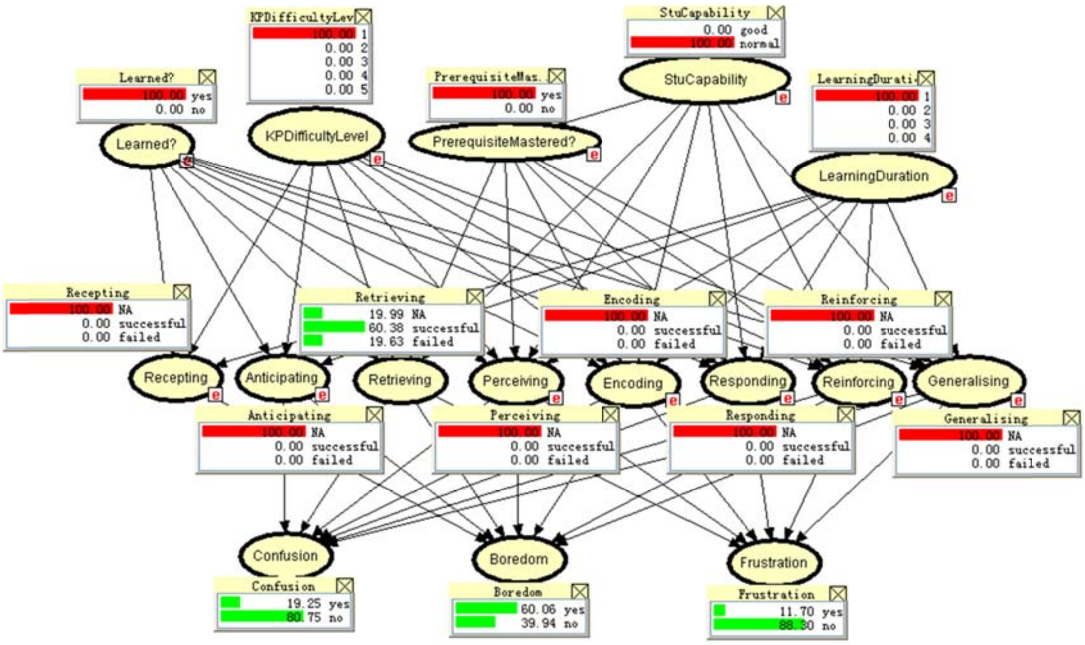

Figure 4-4 Snap shots of the Bayesian network running (case A)

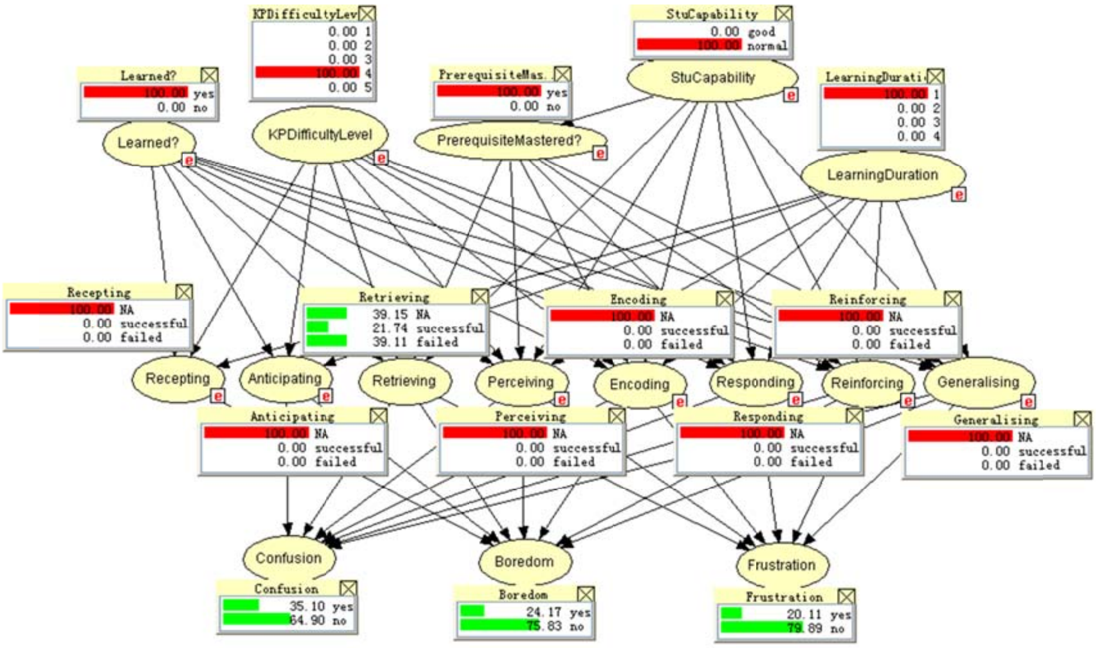

Figure 4-5 Snap shots of the Bayesian network running (case B)

The input nodes are in red color and the output nodes are in green color. Given the evidence in red, the network can infer the probability of the output nodes. The output includes two parts, one is cognitive state, and the other is emotional state. For example in case A, for the cognitive node is “Retrieving”, the probability of the NA state, successful state and failed state are respectively 19.99, 60.38 and 19.63. Only the successful and failed states need to be taken in consideration, because NA (Not Applicable) state is assumed to not appear in this situation. From the probabilities, it is inferred that the state of successful is more probable than failure, therefore the cognitive state is successful retrieving. For the emotional state layer, the probabilities of the state “yes” for the nodes of Confusion, Boredom, and Frustration are respectively 19.25, 60.06 and 11.70. The emotional state which has the maximum value is Boredom, therefore the learner’s emotional state is judged to be Boredom. In case B, the KPDifficulty is 4, the probabilities of the state “yes” for the nodes of

Confusion, Boredom, and Frustration are respectively 35.10, 24.17 and 20.11, therefore the learner's emotional state is judged to be Confusion.

From the BBN network, the student's cognitive and emotional states can be assumed. When both cognitive and emotional states are determined, the specific cause could be determined in terms of the tables which describe emotional states and the related cognitive states in a learning process.

The learner's learning motivation and personality are not included in this model in order to simply the data collection. Those factors could be addressed in future research.

4.5 Emotion feedback model

This section will introduce the emotion feedback model which is designed to generate the feedback to the learners using an Affective computing system on the basis of their emotional state and the learning context information, and how they work. The emotional feedback model consists of two parts, one is an affective ontology and the other is an Influence Diagram. The affective ontology is used to describe the concepts and relationships in an affective learning environment and can be used to query the possible feedback tactics groups. The Influence Diagram is an extended Bayesian network that is used to select the optimal feedback.

4.5.1 Review of modeling techniques in the emotion feedback model

The other central problem in the development of an Affective Learning System is the selection of feedback tactics. The common selection techniques are: rule based selection, and dynamic Bayesian network based selection.

Systems adapting rule based feedback tactic selection include (D'mello et al., 2008, D'Mello et al., 2012, Lahart et al., 2007, Arroyo et al., 2007, Robison et al., 2010, Woolf et al., 2007, Woolf et al., 2009). Several examples in (Woolf et al., 2009), which adapted rules based feedback selection, are:

- if the student is sad/delighted, the agent might look sad/pleased;
- if the student feels bored because he/she cannot do the work, the agent moves to an easier topic and identifies material that the student can accomplish;
- If the student confidence is low, the agent provides encouragement; links performance to student effort and attributes failure to an external issue (hard problem) and success to internal issues (you are doing great), etc.

Instead of using pre-defined heuristic policies, (Woolf et al., 2009) adapted machine learning optimisation algorithms to search for policies for individual students in different affective and cognitive states, with the goal of achieving high learning and positive attitudes towards the subject.

The associated feedback model adapted rule based technique is easy to construct and implement. The possible tutor reactions to student emotions were derived from two sources: theoretical foundations of pedagogy/affect and recommendations made by pedagogical experts (D'mello et al., 2008).

Systems adopting a Bayesian Network feedback tactic include: (Li and Ji, 2005, Hernández et al., 2006, Liao et al., 2006, Murray et al., 2004, Leontidis and Halatsis, 2009).The affective module in (Leontidis and Halatsis, 2009) makes use of an ontological approach in combination with a Bayesian Network (Jensen, 1996) model in order to provide learner with proper affective response. The research work in other literature uses Bayesian Network and Influence Diagrams (Howard and Mateson, 1981) to model the feedback tactics selection.

In addition, developing an ontology is helpful in order to share a common understanding of the structure of information amongst people or software agents; enabling the reuse of domain knowledge; making domain assumptions explicit; separating domain knowledge from the operational knowledge and analyzing domain knowledge (Noy and McGuinness, 2001). Ontology techniques have been adopted in other e-learning research for modeling learners (Ayala, 2009, Nguyen et al., 2011, Ferreira-Satler et al., 2012, Yarandi et al., 2013) and course domain knowledge (Kouneli et al., 2012, Yarandi et al., 2013, Sosnovsky and Gavrilova, 2006). Using an ontology modeling technique to represent the situation in e-learning, including the learner, the course knowledge and the learning process, it is possible to specify the scenarios in e-learning, to share the resources and to infer the relationships in the scenarios. Therefore, using an ontology technique to model the affective learning environment is appropriate for our system.

Next, the modeling technique of Ontology and dynamic Bayesian network based

Influence Diagrams are introduced in detail.

4.5.1.1 Introduction to Ontology

The term ontology originated in the field of philosophy and focuses on the nature of being, existence or reality, as well as the basic categories of being and their relations. An ontology defines the basic terms and relations comprising the vocabulary of a topic area as well as the rules for combining terms and relations to define extensions to the vocabulary (Neches et al., 1991). The term "ontology" in the context of AI can be described by defining a set of representational terms. In such an ontology, definitions associate the names of entities in the universe of discourse (e.g., classes, relations, functions, or other objects) with human-readable text describing what the names mean, and formal axioms that constrain the interpretation and well-formed use of these terms (Gruber, 1995).

Current research on constructing an emotion Ontology focuses on the aspects of emotion evidence, emotion detection, emotion expression, emotion classification (Obrenovic et al., 2005, López et al., 2008, Juan-juan, 2010); constructing an emotion Ontology in different languages (Yan et al., 2008, Baldoni et al., 2012); and how to automatically construct an emotion ontology (Ptaszynski et al., 2012, Chong and Zhenyu, 2013, Wei et al., 2012). The ontologies mentioned above only describe the concepts of emotion itself, such as classification, expression, but do not include the response to the emotional state when it appears. Leontidis et al. (2009) make use of an ontological approach to model the learner in order to provide learners with the proper affective guidance. This affective ontology includes the classification of the student's mood, emotion and personality, and the concept of affective tactics, but no description of the relations between the emotional states and the feedback tactics.

Given the analysis of the ontology above and an affective learning environment, there are two problems remaining problems with an ontology based solution:

- Firstly, the learner's cognitive state is not mentioned in the ontology. Cognition and emotion are closely linked and the relationships between them are important to understand a learner's situation in the learning process.
- Secondly, the feedback tactics are not classified clearly and the relationship between the emotional/cognitive state and the feedback are not specified. Organizing the feedback tactics is helpful in providing appropriate and efficient feedback in an affective learning system.

These problems will be improved in the affective learning ontology in this research.

4.5.1.2 Introduction about Dynamic Bayesian Network(DBN) and Influence Diagram(ID)

As mentioned before, a Bayesian Network (BN) is a directed acyclic graph is which each node is annotated with quantitative probability information and it is also called Bayesian belief network (BBN) (Russell et al., 1995). A Dynamic Bayesian Network (DBN) is a Bayesian Network which relates variables to each other over adjacent time steps (Dagum et al., 1995). The main difference between BBN and DBN is that Dynamic Bayesian networks can represent time series or sequences relationship, while BBN only can represent causal relationship. In the emotion model, the emphasis is the causal relationship between the cognitive state and emotional state, so BBN is enough as the modeling tool. In the emotion feedback model, it is necessary to consider the time series relationship before and after feedback, therefore, DBN is an appropriate modeling tool.

An Influence Diagram (ID) (Howard and Matheson, 2005) (also called a relevance diagram, decision diagram or a decision network) is a graphical and mathematical representation of a decision situation. It is a generalization of a Bayesian Network, in which not only probabilistic inference problems but also decision making problems can be modeled and solved. An Influence Diagram can be understood as a Bayesian Network augmented with decision and utility nodes. There are three types of node in an ID: chance node, decision node and utility node. A chance node represents a random variable. A decision node represents a decision to be made by the user. A utility node represents an additive contribution to the utility function. Each utility node has a utility function that to each configuration of states of its parents associates a utility. By making decisions, the expected utility of each decision alternative and the global utility can be calculated. The alternative with the highest expected utility should be selected; this is the maximum expected utility principle. The Influence Diagram has been widely adopted and is an alternative to a decision tree (Quinlan, 1986) which typically suffers from exponential growth in number of branches with each additional variable modeled.Dynamic decision network (DDN) is a technique that combines decision analysis and Bayesian Networks for real-time. To cope with time varying attributes, DDNs maintain a series of time slices to represent attributes at successive moments in time.

Why is the Influence Diagram (ID) based on Dynamic Bayesian Network (DBN) is a suitable technique to model the feedback tactic selection in Affective learning system? The research in (Li and Ji, 2005, Liao et al., 2006) stated that the development of an affective learning system has the challenges below:

1) The expression and the measurements of user affect are very much person-dependent and even time or context dependent for the same person.
2) The recognized users' affective states are often ambiguous, uncertain, and incomplete.
3) Users' affective states are dynamic and evolve over time.
4) Both affect recognition and user assistance must be accomplished in a timely and appropriate manner.

An ID based on DBN has several unique advantages. First, it provides a coherent and unified hierarchical probabilistic framework for representing and modeling the uncertain knowledge about user affect and feedback tactics selection. Second, feedback tactics selection is formulated as a decision-making procedure. Third, it incorporates the evolution of user affect and the temporal aspect of decision making with the dynamic structure. The built-in causal and uncertainty representation structure provides powerful capabilities in handling complex situations in practical systems, so such a model is an ideal candidate to accommodate the aforementioned challenges.

In summary of the modeling technique, an ID based on DBN (plus Ontology) are ideal modeling tools to depict the decision process of selecting the feedback. DBN can depict the evolvement when the feedback executed.

4.5.2 Affective learning Ontology

4.5.2.1 The Affective Learning Ontology

Taking account of the problems in the previously presented emotion ontologies and the application requirements of an affective learning system, an affective learning ontology is designed to specify the terms and relations in an affective learning environment, which includes emotion classification, affective feedback tactics, cognitive feedback tactics, instructional step, cognitive step, etc. This ontology model can be used to infer the learner's cognitive state, and query the possible cognitive feedback tactics and affective feedback tactics. With the inclusion of the cognition and instructional step, it is possible to infer the cause of a learner's emotional state. By embracing the cognitive and affective feedback tactics, the model can support the learner from both cognitive and emotional aspects and provide them a good learning experience. The ontology modeling tool deployed in this research is called Protégé which is used to construct domain models and knowledge-based applications with ontologies.

Figure 4-6 presents the main concepts and relations in the affective learning ontology model. There are two parts from the conceptual view, one is about the individual learner, such as learning ability, personality, emotional state and cognitive state, and the other is about the instructional process, such as instructional step, knowledge domain point, and feedback tactics. Figure 4-7 is snapshot of the Ontology model of affective learning ontology developed in OWL.

(1) Concepts related to learner

Student represents a learner in the affective learning environment, Student=<Stu_ID, Name, Age, Sex >. *Stu_ID* is the identifier of a learner. *EmotionalState* is the learner's emotional state, consisting with *NegativeEmotionalState* and *PositiveEmotionalState*.

NegativeEmotionalState = {Boredom, Confusion, Frustration},

PositiveEmotionalState = {Happiness, Interest, Flow}

CognitiveState is the learner's cognitive state during learning process.

CognitiveState={Recepting, Anticipating, Retrieving, Perceiving, Encoding, Responding, Reinforcing, Generalising}.

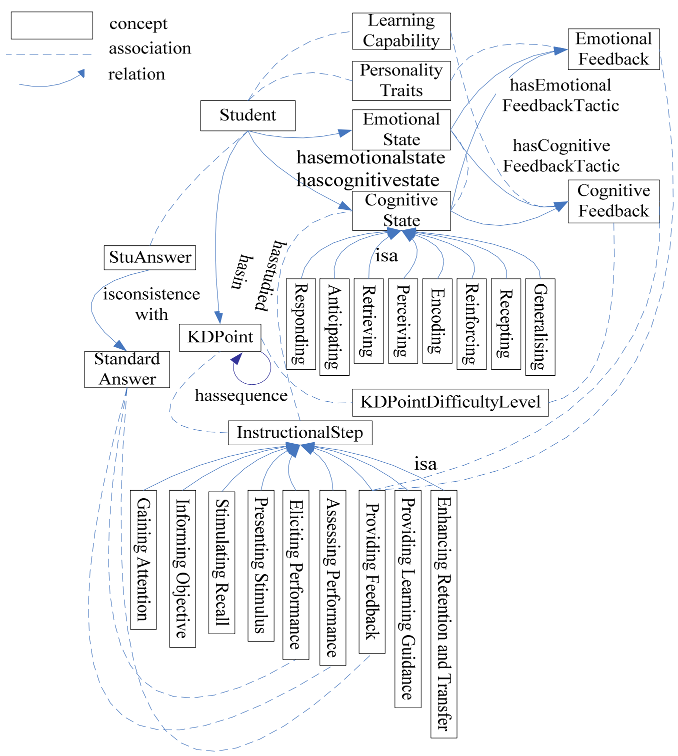

Figure 4-6 The Ontology model of affective learning

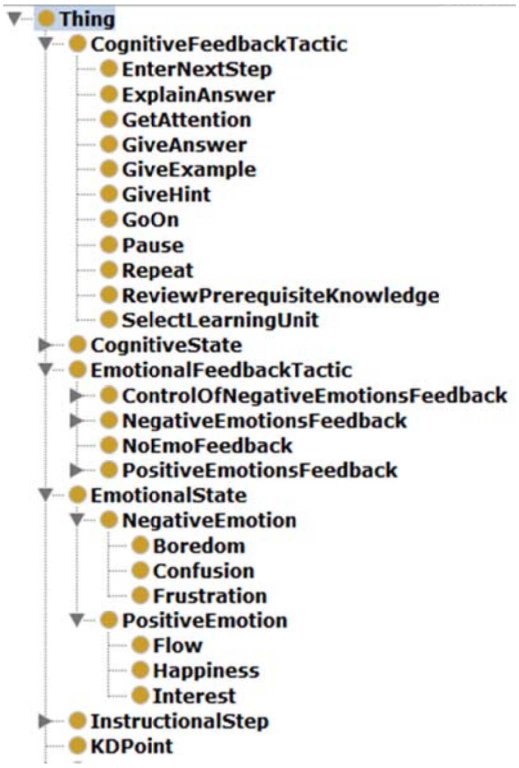

Figure 4-7 Part of the Ontology model of affective learning developed using OWL

(2) Concepts related to instruction

KDPoint means knowledge domain point, *StandardAnswer* means the standard answer of a problem, StuAnswer means the answer given by the student, *InstructionalStep* means instructional step(Gagne et al., 2005). InstructionalStep = {GainingAttention, InformingObjective, StimulatingRecall, PresentingStimulus, ProvidingLearningGuidance, ElicitingPerformance, AssessingPerformance, ProvidingFeedback, EnhancingRetentionandTransfer}. A learning process is divided into nine instructional steps in term of Gagne's theory(Gagne, 1965). Each instructional step is related to corresponding cognitive states.

Concerning the concepts of feedback tactic, *CognitiveFeedback* and *EmotionalFeedback* are defined in this model. *CognitiveFeedback* means responding the learner in the aspect of cognition, such as *GoOn*, *Repeat*, *GiveExample*, *GiveHint*, etc. *EmotionalFeedback* means responding the learner in the aspect of emotion. Economides (2006) defined three categories for the emotional feedback: *PositiveEmotionalFeedback*, *NegativeEmotionalFeedback*, *ControlofNegativeEmotionalFeedback*. *PositiveEmotionalFeedback* acts and expresses positive emotions to the learner trying to develop, maintain and increase his positive emotions, such as *Acceptance*, *Congratulation*, *Reward*, etc. *NegativeEmotionalFeedback* expresses negative emotions to the learner trying to increase his/her effort and commitment, such as Criticism, Punishment. *ControlofNegativeEmotionalFeedback* tries to control the examinee's negative emotions, such as *Sympathy*, *Encouragement*, etc. Robison et al. (2009a) state that an appropriate response could support positive emotions, meanwhile, inappropriate feedback could cause students to transition into very negative emotional states. So, the selection of the feedback tactics should be careful, especially using *NegativeEmotionalFeedback* tactics, which could possibly cause the learner's negative emotional state.

(3) Relations

hasStudied means the student has learned a knowledge domain point, hasStudied={<x， y>|x∈Student∧y∈KDPoint∧x has learned y}.

hasIn means the student is learning a knowledge domain point，*hasIn*={<x， y>|x∈Student∧y∈KDPoint∧x is learning y}.

isInInstructionalStep means the student is an instructional, isInInstructionalStep={<x， y>|x∈Student∧y∈InstructionalStep∧x is in instructional step of y}.

hasSequence means two KDPoints have a sequential relationship, hasSequence={<x，y>|x，y∈KDPoint ∧x is prerequisite of y}.

hasEmotionalFeedbackTactic represents an emotional/cognitive state could be responded to by an emotional feedback tactic; *hasCognitiveFeedbackTactic* represents an emotional /cognitive state could be responded by some cognitive feedback tactic.

4.5.2.2 Reasoning by the affective learning ontology model

On the basis of the concepts and relations in the affective learning ontology model, the learner's situation in learning can be inferred by the rules defined below. With the ontology model embracing emotional state, the cognitive state can be inferred by rules.

Rule 1 Reasoning the rationality of the learning activity

(<Stui, KDPi> ∈hasinhabit)∧(((< KDPi_pre,KDPi> ∈hassequence)∧(<Stui, KDPi_pre> ∈hasstudied)) ∨((<Stui, InformingObjective> ∈isininstructionalstep)∧(<Stui, PositiveEmotionalState> ∈hasemotionalstate)))↦ the learning activity is reasonable, namely the state of anticipating is positive, <anticipating, positive> ∈hasvalue

The learning activity is reasonable when one of the two conditions is satisfied: the first is that the student is learning the KDPi and the student has learned KDPi_pre (the prerequisite of KDPi), and the second is in the InformingObjective step of KDPi, the learner has a positive emotional state, such as happiness, interest and flow. The first condition is based on cognitive aspect, and the second condition is based on emotional aspect. The following rules are also based on cognitive and emotional aspects respectively.

Rule 2 Reasoning mastery state to the prerequisite of KDPi

(<Stui, KDPi> ∈hasInhabit)⋀(<KDPi_pre,KDPi> ∈hasSequence)⋀(<Stui, KDPi_pre> ∈hasStudied)⋀((<StuAnsi_pre,AnsKDPi_pre>∉ isConsistenceWith) ⋁((<Stui, StimulatingRecall > ∈isInInstructionalStep)⋀((<Stui, confusion> ∈hasEmotionalState) ⋁(<Stui, frustration> ∈hasEmotionalState))))↦ the student did not master KDPi_pre, namely the state of retrieving is negative, <retrieving, negative> ∈hasValue.

The student did not master the prerequisite KDPi_pre when one of the two conditions is satisfied: one is student's answer to the problem of KDP_pre is not correct, and the other is in the *StimulatingRecall* step of KDPi, the learner is in confusion or frustration.

Here, the meaning of *perceive*, *comprehend* and *master*, which will be used in following rules, are specified. "*perceive*" means that students can receive the information exposed to him/her. "*comprehend*" means that students can understand and remember what they are to learn. "*master*" means that students can apply what they learned to solve problem.

Rule 3 Reasoning the perception situation to the KDPi

(1) *(<Stui, KDPi> ∈hasInhabit)⋀(<Stui, PresentingStimulus> ∈isInInstructionalStep)⋀ (<Stui,happiness> ∈hasEmotionalState ⋁<Stui,flow> ∈hasEmotionalState)* ↦

The student's perceiving state to KDPi is positive, namely $\langle perceiving, positive\rangle \in hasValue$.

(2) $(\langle Stui, KDPi\rangle \in hasInhabit) \wedge (\langle Stui, PresentingStimulus\rangle \in isInInstructionalStep) \wedge (\langle Stui, confusion\rangle \in hasEmotionalState \vee \langle Stui, frustration\rangle \in hasEmotionalState) \mapsto$ *The perceiving state to KDPi is negative, namely* $\langle perceiving, negative\rangle \in hasValue$.

The student's cognitive state in the *PresentingStimulus* step is *perceiving*. The student perceives KDPi smoothly when he/she is in happiness or flow, conversely the student is stuck at KDPi when he/she is in confusion or frustration.

Rule 4 Reasoning to the comprehension situation to KDPi

(1) $(\langle Stui, KDPi\rangle \in hasInhabit) \wedge (\langle Stui, ProvidingLearningGuidance\rangle \in isIniInstructionalStep) \wedge (\langle Stui, happiness\rangle \in hasEmotionalState \vee \langle Stui, flow\rangle \in hasEmotionalstate) \mapsto$ *The student can understand KDPi, namely* $\langle encoding, positive\rangle \in hasValue$.

(2) $(\langle Stui, KDPi\rangle \in hasInhabit) \wedge (\langle Stui, ProvidingLearningGuidance\rangle \in isInInstructionalStep) \wedge (\langle Stui, confusion\rangle \in hasEmotionalState \vee \langle Stui, frustration\rangle \in hasEmotionalState) \mapsto$ *The student cannot understand KDPi, namely* $\langle encoding, negative\rangle \in hasValue$.

The student's cognitive state in the *ProvidingLearningGuidance* step is encoding. The student can comprehend KDPi when he is in happiness or flow, conversely the student cannot comprehend KDPi when he/she is in confusion or frustration.

Rule 5 Reasoning the mastery situation to KDPi

(1) $(<Stui,KDPi> \in hasInhabit) \wedge (<Stui,ProvidingFeedback> \in isIniInstructionalsStep) \wedge (<Stui,happiness> \in hasEmotionalState \vee <StuAnsi,AnsKDPi> \in isConsistenceWith) \mapsto$ *The student has mastered KDPi, namely* $<reinforcing, positive> \in hasValue$.

(2) $(<Stui,KDPi> \in hasInhabit) \wedge (<Stui,ProvidingFeedback> \in isInInstructionalStep) \wedge (<Stui,confusion> \in hasEmotionalState \vee <Stui,frustration> \in hasEmotionalState \vee <StuAnsi,AnsKDPi> \notin isConsistenceWith) \mapsto$ *The student has mastered KDPi, namely* $<reinforcing,negative> \in hasValue$.

The student's cognitive state in the *ProvidingFeedback* step is reinforcing. The student has mastered the KDPi when he/she is in the happiness state or his/her answer is correct. In contrast, the student has not mastered the KDPi when he/she is in confusion or frustration, or his/her answer is not consistent with the standard.

The reasoning rules above can be used to deduce the cognitive state on the basis of the emotional state, instructional context information, etc. Rule 2 and rule 3 make it possible to obtain the cognitive state without a Question-Answer interaction with the student. With these reasoning rules, emotional states can be transferred to cognitive states and can be used to trigger the feedback mechanism. This is a supplement to the event-driven feedback mechanism in the instructional tutoring system. These rules build the connection between the event-driven feedback and emotion-driven feedback.

The Bayesian network in Figure 4-3 can be used to reason out both the cognitive and emotional state in a probabilistic way, therefore, it is not necessary to use Rule 1 to Rule 5. But for emotion recognition techniques, such as facial expression recognition, user self-report, EEG, etc., these reasoning rules are very helpful to transfer the emotional state to the cognitive state.

When the emotional and cognitive states are known, the appropriate feedback tactics can be queried from the Affective Learning ontology. The next section will explain how to use the ontology to query the appropriate feedback tactics.

4.5.2.3 Query applicative feedback tactics through the Affective Learning ontology

There are two forms of feedback in an Affective Learning System, one is cognitive feedback, and the other is emotional feedback. These two forms of feedback can exist independently or together. Due to the complex intertwined relationship between cognition and emotion, the student's cognitive and emotional states have a respective effect on both cognitive feedback and emotional feedback. The basic process of the query is to collect the information in a scenario, reason out the cognitive state, and determine the feedback tactic. The detailed process is explained below:

Step 1 InfoSet=< Stui, KDPi, instructionalstep, emotionalstate, StuAnsi, AnsKDPi >

//Collecting the information in a learning scenario and saving in InfoSet

Step 2 for(reseaoner_ID=1 to 5)

cognitivestate=reseasoning_service (reseaoner_ID, InfoSet)

//Executing reasoning service from rule 1 to rule 5 in order to obtain the cognitive state

Step 3 A1=∅; A2=∅; B1=∅; B2=∅;

//Initializing feedback tactic selection model

Step 4 *PREFIX EmoOnto:*

http://www.owl-ontologies.com/lab/EmotionOntology.owl #

EmotionalState es=GetEmotionalState();

CognitiveState cs=GetCognitiveState();

A1= SELECT ?emotionalfeedbacktactic WHERE EmoOnto:es

EmoOnto:hasEmotionalFeedbackTactic ?emotionalfeedbacktactic

B1= SELECT ?cognitivefeedbacktactic WHERE EmoOnto:es

EmoOnto:hasCognitiveFeedbackTactic ? cognitivefeedbacktactic

A2= SELECT ?emotionalfeedbacktactic WHERE EmoOnto:cs

EmoOnto:hasEmotionalFeedbackTactic ?emotionalfeedbacktactic

B2= SELECT ? cognitivefeedbacktactic WHERE EmoOnto:cs

EmoOnto:hasCognitiveFeedbackTactic ? cognitivefeedbacktactic

//With SPARQL[3] to query using the relationship of *hasEmotionalFeedbackTactic* and *hasCognitiveFeedbackTactic*, and saving the results in set A1, A2, B1, B2. Table 4-10 and Table 4-11 present the relationship between the emotional/cognitive states and affective/ cognitive feedback tactics.

Step 5 *CognitiveFeedback = A1∩A2;*

EmotionalFeedback = B1∩B2;

Result={CognitiveFeedback}+{EmotionalFeedback};

//Save the result after the intersection operation

[3] SPARQL (SPARQL Protocol and RDF Query Language) is an RDF query language, that is, a semantic query language for databases, able to retrieve and manipulate data stored in Resource Description Framework (RDF) format.

Table 4-10 The relationship between emotional state and emotional/cognitive feedback tactics

Emotional State	Affective feedback tactics	Cognitive feedback tactics
Interest	praise, encouragement,noemofeedback	GoOn
Happiness	Congratulation, encouragement, goodwill, positivesurprise, praise, reward, noemofeedback	GoOn
Flow	Congratulation, encouragement, praise, reward, noemofeedback	GoOn
Confusion	Relief, Encouragement, Sympathy	Pause, GiveHint, Repeat, GiveExample, SelectingLearningUnit, Explain answer, Give Answer, ReviewPrerequisiteKP
Frustration	Encouragement, goodwill, relief, sympathy	Explainanswer, Giveanswer, Giveexample, Givehint, Repeat, ReviewprerequisiteKP, SelectLearningUnit
Boredom	Acceptance, criticism, encouragement, positivesurprise, relief, sympathy	EnterNextStep, ExplainAnswer, GetAttention, GiveAnswer, GiveExample, GiveHint, ReviewPrerequisiteKP, selectLearningUnit,

Table 4-11 The relationship between cognitive state and emotional/cognitive feedback tactics

Cognitive State	Affective feedback tactics	Cognitive feedback tactics
Recepting	Criticism, praise, noemofeedback	goon, getattention
Anticipating	Acceptance, encouragement, goodwill, relief, noemofeedback	Goon, selectlearningunit
Retrieving	Sympathy, Praise, Acceptance, Relief, Encouragement, noemofeedback	Pause, Repeat, Enter next step, GoOn, ReviewPrerequisiteKP
Perceiving	Praise, Relief, Encouragement, Acceptance, noemofeedback	Repeat, GiveExample, EnterNextStep, ReviewPrerequisiteKP, GoOn
Encoding	Acceptance, encouragement, positivesurprise, praise, relief, noemofeedback	EnterNextStep, GiveExample, GoOn, Pause, Repeat, ReviewPrerequisiteKP
Responding	Acceptance, encouragement, goodwill, positivesurprise, relief, sympathy, noemofeedback	EnterNextStep, GiveAnswer, GiveHint, GoOn, Pause, ReviewPrerequisiteKP
Reinforcing	Acceptance, congratulation, encouragement, positivesurprise, praise, relief, reward, sympathy, noemofeedback	EnterNexStep,ExplainAnswer, GoOn, Pause
Generalising	Acceptance, encouragement, positivesurprise, praise, relief, sympathy, noemofeedback	Enternextstep, giveexample, goon, pause, repeat, reviewprerequisiteKP

The applicative affective/cognitive feedback tactics are generated through the query operation. The result could be several tactics in affective/cognitive feedback tactics set, so an Influence diagram model is designed to select the optimal affective/cognitive feedback tactics group. The Influence diagram model will be introduced in the following section.

4.5.3 Feedback tactic selection Influence Diagram Model

The feedbacktactic selection influence diagram model is used to select the optimal affective/cognitive feedback tactics group, and the design of this model mainly focuses the situations when negative emotional states appear. Figure 4-8 describes how a student's cognitive/emotional states are impacted by affective feedback and cognitive feedback between time slots ti to ti+2. Time slot could be defined based on fixed time intervals, such as every 5 or 10 seconds. Or it could be defined based on the event, for example, in this study, one time slot could be the time interval when the affective feedback happens or when the cognitive feedback happens. Figure 4-8 is derived from Figure2-2 by splitting affective feedback and cognitive feedback into ti+1 and ti+2 respectively. Assume the affective feedback occurs at ti+1and the cognitive feedback occurs at ti+2. *Cognitive Cost* represents the cost of cognitive feedback, *Cognitive Utility* represents the utility in cognitive aspect, *Affective Utility* represents the utility in emotional aspect, *General Utility* represents the sum of the *Cognitive Utility* and *Affective Utility*. This model only describes the feedback towards negative emotional states.

This ID model describes the relations below:

1) *Affective feedback* has impact on *Affective State* at ti+1
2) *Cognitive feedback* has impact on *Cognitive State* at ti+2
3) *Affective State* at ti+1 has impact on *Affective State* and *Cognitive State* at ti+2
4) *Cognitive feedback* has impact on *Affective State* in each moment
5) *Cognitive feedback* and *Affective feedback* in each time slot has respectively

impact on *Cognitive feedback* and *Affective feedback* in next moment.

6) *Affective feedback* is provided at ti+1 and *Cognitive feedback* is provided at ti+2. Providing *Affective feedback* prior to *Cognitive feedback* is more reasonable because this could let the student at a good emotional state to accept the *Cognitive feedback* and achieve better learning effect.

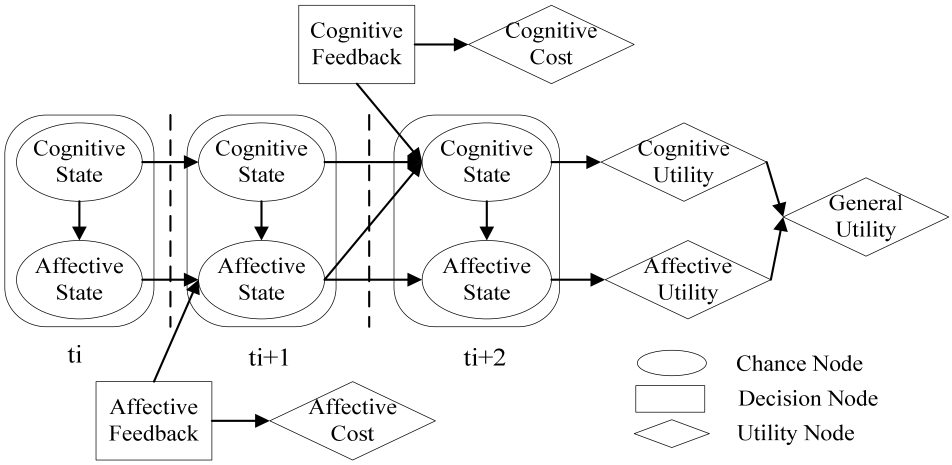

Figure 4-8 The top level of the feedback tactic selection model

The applicative cognitive feedback tactic set and affective feedback tactic set can be queried through the Affective Learning ontology as section of 4.5.2.3 addressed. The applicative cognitive/affective feedback tactics are respectively imported into the decision node Cognitive Feedback and Affective Feedback in Figure 4-8 as the decision. The feedback tactic selection model is designed in order to select the cognitive/affective pair with optimal utility from the cognitive feedback tactic set and the affective feedback tactic set. In general, there are two types of feedback in learning theory (Hausmann et al., 2013), one is based on the self-remediation hypothesis which predicts that learning is maximized when learners attempt to correct their own errors, and the other is based on the tutor-remediation hypothesis which predicts that students learn best when a tutoring system immediately explains why an entry is incorrect. In order to precisely specify the process for making the optimum choice, five definitions are given below:

Definition 1：Affective Cost means the cost caused by affective feedback, for example time cost, the time spend on giving feedback to the student on affective aspect.

Definition 2: Affective Utility means the decreased amount of negative emotional state or the increased amount of positive emotional state in an affective state node. This amount can be measured by calculating the difference value between the affective state probability on ti and on ti+1, P_{ti+1}(AffectiveSate)- P_{ti}(AffectiveSate).

Definition 3: Cognitive Cost can be understood from two aspects, one is how much cognitive support the system provides ($Cost_{sys}$), and the other is how much effort the student contributes ($Cost_{stu}$), including time and vigor. Assume $Cost_{sys}+Cost_{stu}= c$**,** c is a constant. The more cognitive support the system provides the less effort the student contributes. In contrast the less cognitive support the system provides, the more effort the student contributes. $Cost_{stu}$ is adopted to measure the cognitive cost in this model. On the basis of the self-remediation hypothesis, that learning is maximized when learners attempt to correct their own errors, so the more effort the student contributes ($Cost_{stu}$), the more learning utility achieved.

$Cost_{stu}$ has different values corresponding to different cognitive feedback tactics. For example, for the tactic of *pause*, the system provides no cognitive support and the student needs to pay most effort, the value is set to be 50; and to the *givehint* tactic, the system provides cognitive support by giving a hint and the student contributes less effort, the value is set to be 30.

Definition 4: Cognitive Utility means the decreased amount of negative cognitive state or the increased amount of positive cognitive state in a cognitive state node. This amount can be measured by calculating the difference value between the cognitive state probability on ti+1 and on ti+2, P_{ti+2}(CognitiveSate)-P_{ti+1}(CognitiveSate). In terms of the tutor-remediation hypothesis, the more cognitive support the system provides, the more cognitive utility the student earns. So, with the feedback tactics that the system provides more cognitive support will cause a higher probability of a successful cognitive state.

The Cognitive Cost in Definition 3 and the Cognitive Utility in Definition 4 are a pair opposing measures, the more cognitive support the system provides, the less effort the student contributes ($Cost_{stu}$), but the more cognitive utility the student probably earns. On the contrary, the less cognitive support the system provides, the more effort the student contributes ($Cost_{stu}$), but the less cognitive utility the student probably earns.

Definition 5: General Utility is the sum of Cognitive Utility, Cognitive cost, Affective Utility and Affective cost.

Assume the cognitive and affective states at ti are known, and the cognitive state at ti+1 is unchangeable, these three nodes are removed for simplifying the complexity of the CPT in the model. Additionally, three probability nodes, *StuCapability*, *KPDifficulty* and *PrerequisiteMastered* are added for describing the impact of the student's individual and the learning content to the learning process. After the simplification and supplement, the feedback tactic selection model is shown in Figure

4-9.

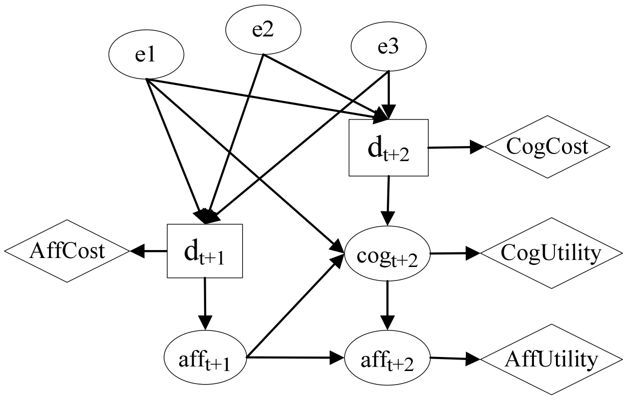

Figure 4-9 The cognitive and affective feedback tactic selection model

Assume $\varDelta$=（e_1, e_2, e_3, d_{t+1}, d_{t+2}）, e1, e2, e3 represent *StuCapability*, *KPDifficulty* and *PrerequisiteMastered* respectively, and the value of these nodes are known. Decision nodes d_{t+1} and d_{t+2} represent affective feedback tactic and cognitive feedback tactic. The optimal utility decision $\varDelta^*$ is the cognitive feedback tactic and affective feedback tactic pair that maximizes Expected Utility (EU).

$$\varDelta^* = \arg \max_{(d^*_{t+1}, d^*_{t+2})} \mathrm{EU}_{\varDelta} \qquad \text{(Equation 4-4)}$$

$$\begin{aligned}\mathrm{EU}_{\varDelta\max} &= p_{\varDelta}(aff)g_{ua}(aff) + p_{\varDelta}(d^*_{t+1})g_{ca}(aff) \\ &+ p_{\varDelta}(cog)g_{uc}(cog) + p_{\varDelta}(d^*_{t+2})g_{cc}(cog)\end{aligned} \qquad \text{(Equation 4-5)}$$

In the formulas, aff and cog means affective state and cognitive state respectively, d*t+1 and d*t+2 the item in applicative cognitive feedback tactic set and affective feedback tactic set queried from the affective learning ontology model. g_{ua}(*Aff*) and g_{ca}(*Aff*) are affective utility function and affective cost function respectively, g_{uc}(*cog*) and g_{cc}(*cog*) are cognitive utility and cognitive cost function.

4.5.4 An algorithm which produces utility optimal instructional feedback tactics based on the self-remediation hypothesis

4.5.4.1 Algorithm 1 description

The algorithm which produces utility optimal instructional feedback tactics based on the self-remediation hypothesis is called Algorithm 1. The basic idea is to make the student learning by self-remediation to the greatest extent. The main procedure of the algorithm is: Firstly, to initialize the cognitive and affective nodes in the feedback network model, and to import the applicative cognitive feedback tactics set and affective feedback tactics set. Secondly, to input the proof provided in the learning scenario into the decision network, and to instantiate the decision node in chronological order. Thirdly, to compute the conditional expected utility (EU), and to traverse all the combination of cognitive and affective feedback tactics. Finally, the cognitive and affective feedback tactic pair corresponding the maximum conditional expected utility (EU_{max}) is the result. The detailed steps are addressed below:

Step 1 Reasoning the ontology and produce the applicative cognitive/affective feedback tactics set.

Step 2 If the emotional state is negative then go to Step 3 else go to Step 11.

Step 3 If the item number in any one of the applicative feedback tactics set is equal or greater than 2, then go to step 4), else go to step 12.

Step 4 Generating a feedback decision model:

a) loading the influence diagram model.

b) loading cognitive states and emotional states.

c) loading cognitive feedback tactics set and affective feedback tactics set as the action states of the cognitive decision node and affective decision node respectively.

d) loading utility function and cost function.

e) loading CPTs.

Step 5 Collecting the value for nodes e1, e2, e3.

Step 6 Instantiating the decision variable d_{t+1} using the first action in terms of the time order.

Step 7 Entering the decision variable d_{t+2} under the constrain of the decision variable d_{t+1}, and calculating the conditional expected utility U for each decision action in d_{t+2}.

Step 8 Returning to the decision variable d_{t+1} and instantiating it using the second action, and loop executing Step 7 until all the actions in the decision variable d_{t+1} have been executed.

Step 9 Finding the maximum conditional expected utility U*max* and outputting its responding affective feedback tactic d^*_{t+1} and cognitive feedback tactic d^*_{t+2}.

Step 10 If the cognitive feedback tactic d^*_{t+2} is *giveexample* and no related example, then finding the next maximum conditional expected utility U*max* and outputting its responding affective feedback tactic d^*_{t+1} and cognitive feedback tactic d^*_{t+2} , go to Step 12.

Step 11 Select one cognitive and one affective feedback tactic from the applicative cognitive/affective feedback tactics set randomly.

Step 12 End.

4.5.4.2 Case study about the algorithm 1

This section describes an example of how to use the algorithm 1 to select the optimal cognitive and affective feedback tactics. Assume the affective and cognitive state are Perceiving and Confusion and are loaded in to *cog* and *aff* node in the decision network respectively. Through the query to the affective ontology, the applicative affective feedback tactics set is {relief, sympathy, encouragement} and the applicative cognitive feedback tactics set is {pause, giveexample, reviewprerequisiteKP, repeat}. The actions loaded to node d_{t+1} is {relief, sympathy, encouragement} and the actions loaded to node d_{t+2} is {pause, giveexample, reviewprerequisiteKP, repeat}. Load the Conditional Probability Table (CPT) into the decision network. Parts of CPTs are listed below:

Table 4-12 CPT of d_{t+1} $P(d_{t+1}|e1,e2,e3)$

e3	easy				hard			
e2	yes		no		yes		no	
e1	g	n	g	n	g	n	g	n
rel	0.0	0.3	0.6	0.6	0.33	0.33	0.6	0.6
sym	0.0	0.6	0.2	0.2	0.33	0.33	0.1	0.1
enco	1.0	0.1	0.2	0.2	0.33	0.33	0.3	0.3

Table 4-13 CPT of dt+2 P(dt+2|e1,e2,e3)

e3	easy				hard			
e2	yes		no		yes		no	
e1	g	n	g	n	g	n	g	n
rep	0.0	0.5	0.25	0.25	0.33	0.5	0.2	0.2
gex	0.0	0.5	0.25	0.25	0.33	0.5	0.2	0.2
repre	0.0	0.0	0.5	0.5	0.0	0.0	0.4	0.4
pau	1.0	0.0	0.0	0.0	0.33	0.0	0.2	0.2

Table 4-14 CPT of afft+1 P(afft+1| dt+1)

d_{t+1}	rel	enco	sym
yes	0.3	0.4	0.9
no	0.7	0.6	0.1

Table 4-15 CPT of cogt+2 P(cogt+2|afft+1,e1,dt+2)

e1			**good**									**normal**				
aff t+1		yes				no				yes				no		
d t+2	rep	gex	repre	pau	rep	gex	repre	pau	rep	gex	repre	pau	rep	gex	repre	pau
Succes	0.6	0.7	0.7	0.8	0.8	0.9	0.9	0.9	0.5	0.6	0.6	0.5	0.7	0.8	0.8	0.6
failed	0.4	0.3	0.3	0.2	0.2	0.1	0.1	0.1	0.5	0.4	0.4	0.5	0.3	0.2	0.2	0.4

g_{ua}(Aff) and g_{ca}(Aff) are affective utility function and affective cost function. Assume the affective costs for each action are the same and not counted in the calculation, set g_{ca}(Aff)=0. The design of g_{ua}(Aff) considers mainly to the utility of negative emotional state, if affstate=yes，the utility is set to be -100, on the contrary, the values is set to be 0.

$$g_{ua}\left(Aff\right)=\begin{cases}-100 & affstate=yes\\ 0 & affstate=no\end{cases} \quad \text{(Equation 4-6)}$$

The total cognitive utility comprises the cognitive utility g_{uc}(cog) and cognitive cost g_{cc}(cog). g_{uc}(cog) represents the utility produced by the cognitive state itself, and g_{cc}(cog) represents the utility produced by different cognitive feedback tactics. For example, in cognitive feedback tactics set {pause, giveexample, reviewprerequisiteKP, repeat}, according to Definition 3, the cost value of each cognitive feedback tactic is set to be {50, 45, 40, 45} in turn.

$$g_{uc}\left(cog\right)=\begin{cases}50 & cogstate=successful\\ 0 & cogstate=failed\end{cases} \quad \text{(Equation 4-7)}$$

$$g_{cc}\left(cog\right)=\begin{cases}45 & d_{t+2}=repeat\\ 45 & d_{t+2}=giveexample\\ 40 & d_{t+2}=reviewprerequisitekp\\ 50 & d_{t+2}=pause\end{cases} \quad \text{(Equation 4-8)}$$

The procedure of computing EU(⊿) and the optimal feedback tactics decision are presented below:

Assume Δ=(e_1, e_2, e_3, d_{t+1}, d_{t+2}), p(e1=g)=0.85, p(e2=y)=0.9, p(e3=easy)=0.8. All the values of EU are calculated using all different combination in action in d_{t+1} and d_{t+2}.

Table 4-16 The table of EU values with actions in d_{t+1} and d_{t+2}

d_{t+1}	d_{t+2}	EU(Δ)
encouragement	giveexample	66.39
encouragement	pause	72.97
encouragement	repeat	52.99
encouragement	reviewprerequisiteKP	61.39
relief	giveexample	69.8
relief	pause	75.02
relief	repeat	56.51
relief	reviewprerequisiteKP	64.8
sympathy	giveexample	49.32
sympathy	pause	62.74
sympathy	repeat	35.41
sympathy	reviewprerequisitekp	44.32

It can be seen from Table 4-16 that EU(Δ)max=75.02, the optimal decision is d_{t+1}= relief, and d_{t+2} =pause.

In Table 4-17, a group of cases calculating with Algorithm 1 are listed.

Table 4-17 A group of cases calculating with Algorithm 1

id	Affective State	Cognitive State	PrerequisiteKP mastered level	Difficulty level	Learning ability level	Cognitive feedback tactic	Affective feedback tactic
1	Confusion	Perceiving	yes=0.9	easy=0.85	good=0.95	pause	encouragement
2	Confusion	Retrieving	no=0.85	hard=0.8	normal=0.9	pause	encouragement
3	Confusion	Encoding	yes=0.8	hard=0.85	normal=1	giveexample	relief
4	Boredom	Retrieving	yes	easy	normal	enternextstep	acceptance
5	Confusion	Encoding	no=0.8	hard=0.8	good=0.8	pause	relief
6	Boredom	Retrieving	yes	easy	good	enternextstep	acceptance
7	Confusion	Encoding	yes=0.5	hard=0.9	good=0.5	pause	relief
8	Frustration	Encoding	no	hard	normal	reviewprerequisite KP	sympathy

From the cases above, it can be seen that Algorithm 1 is effective, but it still does not give enough consideration to the student's personal information. For example, case 2 and case 5, adapting the *pause* tactic can maximize the utility but this will also probably cause student failure in cognition because lack of sufficient consideration of the fact that the student did not master the PrerequisiteKP very well.

In case 2, PrerequisiteKP mastered level no=0.85, Difficulty level hard=0.8, Learning ability level normal=0.9.

In case 5, PrerequisiteKP mastered level no=0.8, Difficulty level hard=0.8, Learning ability level good=0.8.

On the basis of teaching experiences, the student in case 2 probably will encounter cognitive failure due to the poor PrerequisiteKP mastered level, hard Difficulty level and low Learning ability level. The student in case 5 has better learning ability, but he still probably will face cognitive failure due to the poor PrerequisiteKP mastered level, hard Difficulty level. Therefore, a feedback tactic decision algorithm based on the tutor-remediation hypothesis was designed.

4.5.5 An algorithm to produce utility optimal instructional feedback tactics based on tutor-remediation hypothesis

4.5.5.1 Algorithm 2 description

The improved algorithm is called algorithm 2, which is based on algorithm 1 and places more emphasis on the tutor's experience. Algorithm 2 tends to the tutor-remediation hypothesis more than algorithm 1. The basic idea is to intervene and feedback to the student on the basis of tutor' experience first, then the learning utility. So, algorithm 2 needs to consider not only the utility of each feedback tactic pair, but also the tutor's experience of the situations.

What is improved in algorithm 2 is adding a step to calculate the expectation of each feedback tactic when a learning situation is given, and select the feedback tactic(s) with the maximum expectation. After working out $h1_{max}$ and $h2_{max}$, if more than one feedback tactics have the same maximum expectation, then the utility optimal instructional feedback tactics decision process of algorithm 2 will be adopted to select the optimal feedback tactic pair d^*_{t+1} and d^*_{t+2} under constraint of $h1_{max}$ and $h2_{max}$. Assume $h1 \in$ actions of d_{t+1}, $h2 \in$ actions of d_{t+2}, then

$$h1_{\max} = \arg\max_{h1 \in d_{t+1}} P(h1|e_1, e_2, e_3)$$

(Equation 4-8)

$$h2_{\max} = \arg\max_{h2 \in d_{t+2}} P(h2|e_1, e_2, e_3)$$ (Equation 4-9)

The steps in algorithm 2 are addressed below:

Step 1 Reasoning the ontology and produce the possible feedback tactics set in d_{t+1} and d_{t+2}.

Step 2 If the emotional state is negative then go to Step 3 else go to Step 7.

Step 3 If the item number in any one of the applicative feedback tactics set is equal or greater than 2, then go to step 4), else end.

Step 4 Generating a feedback decision model.

Step 5 Collecting the value for nodes e1, e2, e3.

Step 6 Calculating $h1_{max}$ and $h2_{max}$.

if $h1_{max}$ and $h2_{max}$ or both unique respectively,

$d^*_{t+1} = h1_{max}$ $d^*_{t+2} = h2_{max}$

else

under the constrain of $h1_{max}$ and $h2_{max}$, execute Step 6) to Step 10) in Algorithm 1 to work out d^*_{t+1} and d^*_{t+2}

Step 7 Select one cognitive and one affective feedback tactic from the applicative cognitive/affective feedback tactics set randomly.

Step 8 End.

4.5.5.2 Case study about the algorithm 2

In Table 4-18, a group of cases calculating with Algorithm 2 are listed.

Table 4-18 A group of cases calculating with Algorithm 2

id	Affective State	Cognitive State	Prerequisite KP mastered level	Difficulty level	Learning ability level	Cognitive feedback tactic	Affective feedback tactic
1	Confusion	Perceiving	yes=0.9	easy=0.85	good=0.95	pause	encouragement
2	Confusion	Retrieving	no=0.85	hard=0.8	normal=0.9	*reviewprerequi siteKP	*relief
3	Confusion	Encoding	yes=0.8	hard=0.85	normal=1	giveexample	relief
4	Boredom	Retrieving	yes	easy	normal	enternextstep	acceptance
5	Confusion	Encoding	no=0.8	hard=0.8	good=0.8	*reviewprerequi -siteKP	relief
6	Boredom	Retrieving	yes	easy	good	enternextstep	acceptance
7	Confusion	Encoding	yes=0.5	hard=0.9	good=0.5	*giveexample	relief
8	Frustration	Encoding	no	hard	normal	Reviewprerequi -siteKP	sympathy

The items with * in Table are the different results after adopting the improved algorithm 2. It can be seen that the feedback tactics produced by the improved algorithm 2, are tend more to tutor-remediation rather than self-remediation as in algorithm 1. For example, when the student did not master the prerequisite knowledge point well, the system will provide *review* or *giveexample* to support the student in order to avoid the cognitive failure on the basis of the judgment of the tutor's experience.

4.6 Summary

This chapter introduced the modeling process of the emotion analysis model and feedback model. The emotion analysis model is used to classify the negative emotion into a specified emotional state and could be used to deduce the learner's cognitive state. The emotion analysis model is constructed by a Bayesian belief network, which uses the student's background information and learning contextual information as input and deduces the specified negative emotional state. The emotion feedback model is designed to generate the feedback to the learners of an Affective computing system on the basis of their emotional state and the learning context information. The emotional feedback model consists of two parts, one is an affective ontology and the other is an influence diagram. The affective ontology is used to describe the concepts and relationships in an affective learning environment and can be used to query the possible feedback tactics groups. The Influence diagram is an extended Bayesian network that is used to select the optimal feedback. There are two algorithms designed on the basis of the emotion feedback model, called Algorithm 1 and Algorithm 2 respectively. Algorithm 1 produces utility optimal instructional feedback tactics based on the self-remediation hypothesis. Algorithm 2 is based on algorithm 1 and places more emphasis on the tutor's experience, which tends towards the tutor-remediation hypothesis. Case studies for both algorithms were presented.

Chapter 5

Evaluation

This evaluation study focuses on the emotion analysis model and emotion feedback model presented in chapter 4, and these two models are evaluated independently and jointly. The evaluation consist of three stages – Stage1: Evaluation of the emotion analysis model; Stage 2: Evaluation of the emotion feedback model; Stage 3: The evaluation of the two models combined. Figure 5-1 shows the range of the three stages in the Affective learning system and Figure 5-2 shows a running snap shot of the evaluation system which is used in stage 2 and 3. The evaluation system was developed using MyEclipse, Adobe Flash Builder 4, the server is Tomcat 6.0, and the database is MySQL Server 5.0. The system was published online and the evaluators conduct the evaluation using the Firefox browser.

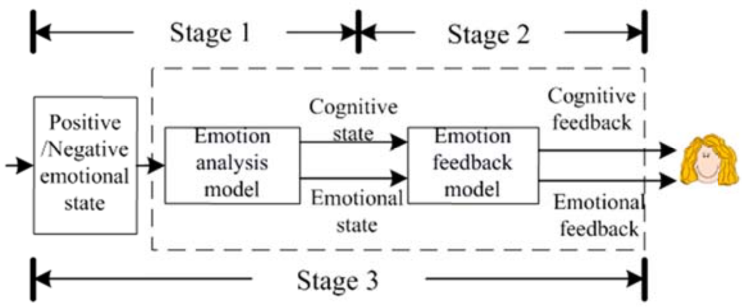

Figure 5-1Three evaluation stages to the models in the Affective learning system

Figure 5-2 The interface of the evaluation system which is used in stage 2 and stage 3

5.1 Stage 1

The aim of evaluation 1 is to evaluate the emotion analysis model. The goal of the emotion analysis model is to classify the negative emotion into specified emotional state and can be used to deduce the learner's cognitive state. This model is constructed by a Bayesian belief network, which uses the student's background information and learning contextual information as input and deduces the specified negative emotional state. The positive emotional states are treated as one emotional state and are not classified further because the positive emotional states are mapped to the same cognitive state and have the same feedback tactics according to the results in observation study, see Table 4-1 to 4-9. From these tables, it can be seen that the cognitive state that causes the positive emotional state is unique. Therefore, all the cases in this evaluation are related to the negative emotional states. The evaluation hypothesis, data, method and results are presented below.

5.1.1 Experimental hypothesis

The experiment hypotheses for evaluation in Stage 1 are proposed:

H0: An emotion analysis model can be used to classify negative emotion and hence deduce the learner's cognitive state.

H1: An emotion analysis model cannot be used to classify negative emotion and hence deduce the learner's cognitive state.

5.1.2 Data

The data set that are used to evaluate the emotion analysis model are the same data that was used to learn the parameters in the Bayesian belief network. The original data came from the video study in Chapter 3 and the production process of the cases set was addressed in section 4.4.5 in detail. In this data set, the specified emotional and cognitive states came from the stimulated reports by students themselves in the video study. And this data set is used to train the parameters in the emotion analysis model and evaluate the accuracy of the emotion analysis model. The detailed method is addressed in section 5.1.3. The student's information and the learning contextual information are fed into the Bayesian belief network and the network deduces the specified negative emotional state and cognitive state.

5.1.3 Method

The training data set and the validation data set are the same set, and the model was trained and validated using 10-fold cross-validation (Kohavi, 1995). With this method, the model is trained on data from 90% of the students and is then evaluated for accuracy on the remaining 10%. The 10-fold cross-validation method is repeated ten times to achieve an average value. In this evaluation, the group id of ten groups are 1, 2, ……, 10 respectively. A new group of training data set and validation data set are produced each time. In each group, 90% data selected randomly from the whole data set form the training data set and the remaining 10% data are used to as evaluation data.

5.1.4 Results

The accuracy rate for ten groups (group id is 1, 2, ……, 10 respectively) in the evaluation respectively to the emotional state and to both emotional state and cognitive state are presented in Table 5-1 and Table 5-2.

Table 5-1 A summary of accuracy rate for ten groups in the evaluation to the emotional state in stage 1

Group id	accuracy rate
1	70.59%
2	64.71%
3	64.71%
4	52.94%
5	64.71%
6	58.82%
7	58.82%
8	52.94%
9	52.94%
10	58.82%
Average accuracy rate	60.00%

Table 5-2 A summary of accuracy rate for ten groups in the evaluation to the emotional state and cognitive state in stage 1

Group id	accuracy rate
1	64.71%
2	52.94%
3	64.71%
4	47.06%
5	41.18%
6	47.06%
7	35.29%
8	41.18%
9	52.94%
10	41.18%
Average accuracy rate	48.82%

With the method of ten times 10-fold cross-validation, evaluation results showed that the Bayesian network classifies the emotion state with 60% accuracy and classifies both the emotion and cognitive state with 48.82% accuracy. There are 3 emotional states and 2 cognitive state (successful or failed) in stage 1, therefore the accuracy by random selection would be respectively are 33.3% and 16.7% accurate. So, hypothesis H0, an emotion analysis model can be used to classify negative emotion and hence deduce the learner's cognitive state, is supported.

5.2 Stage 2

The aim of Stage2 is to evaluate the emotion feedback model. The goal of the emotion feedback model is to produce the most appropriate cognitive and emotional feedback tactics pairing group to the student on the basis the student's information and learning contextual information. The design of the feedback model adopts the Ontology technique and the Influence Diagram technique. The feedback model consists of an emotion ontology and an influence diagram. The emotion ontology describes the relationship between the emotional states and feedback tactics and the relationship between the cognitive states and feedback tactics. The possible emotional and cognitive feedback tactics can be obtained from the ontology using the student's emotional state and cognitive state as the input condition. The ontology was imported in a MySQL database, and it could be queried by SPARQL in Jena. Also the ontology can be queried in Protege by DL Query or SPARQL Query. In this research, the applicative emotional and cognitive feedback tactics are queried out in Protege and imported to the evaluation system. The feedback tactic selection network is an Influence Diagram which is a Bayesian network embracing decision nodes and utility nodes. The possible feedback tactics obtained from the emotion ontology form the items in the emotional feedback decision node and cognitive feedback decision node separately in the feedback selection network. This network can select the optimal emotional and cognitive feedback tactic pairing group under Algorithm A1 or Algorithm A2 (See Chapter 4) in terms of the student's information and learning contextual information. The structure of the network is described in Figure 4-2-3. In order to implement the network, the network model needs to be instantiated in terms of specific combinations of cognitive and emotional state. Algorithm A2 selects the optimal feedback tactic considering the maximum probability value of the feedback node first, then the maximum global utility, while Algorithm A1 only considers the maximum global utility. Algorithm A2 is designed on the basis of the tutor-remediation hypothesis while the Algorithm A1 is on the basis of the self-remediation hypothesis (Hausmann et al., 2013). In Stage 2, an experiment was designed in order to identify which algorithm is better in the light of the tutor's experience.

Figure 5-3 Evaluation page of the evaluation system in stage 2

5.2.1 Experimental hypothesis

The experiment hypotheses for evaluation in Stage 2 are proposed:

H0: The degree of satisfaction to the feedback based on tutor-remediation hypothesis (produced by Algorithm A2) is higher than the feedback based on self-remediation hypothesis (produced by Algorithm A1).

H1: The degree of satisfaction to the feedback based on tutor-remediation hypothesis (produced by Algorithm A2) is not higher than the feedback based on self-remediation hypothesis (produced by Algorithm A1).

5.2.2 Method

The model was evaluated by four experienced C-programming tutors. An evaluation platform was developed as a website and it was used to present the instructional material, student's information and feedback to the evaluators, and also collect the evaluation results. Each tutor was presented with the same cases. A lecture about "Array and Pointer" was selected as the instructional material and 18 video clips were extracted to construct cases. Each case consists of a video clip, student's background information constructed by hand, and corresponding three types of feedback. The feedback f1 and feedback f2 are produced by Algorithm A2 and Algorithm A1 separately. Additional to these two types of feedback, another type of feedback f3, that is a less likely response, is constructed by hand. This evaluation method is described in (Porayska-Pomsta and Pain, 2004). The evaluation data, participants and evaluation process are described in detail as follows.

5.2.3 Evaluation Data

The content of the instructional video used in the evaluation describes how pointers could be used to operate on elements in an array. This material forms part of an intermediate or advanced part of a course on the C programming language and relies on prior knowledge acquired earlier in the course. The video was taught by a female tutor and it is 31 minutes long. The tutor's face does not appear in the video, only her voice and her computer screen appear. Her computer screen is used to display the slides and the program implementation. 18 clips were selected from this video, ranging from 5 to 51 seconds in length. In total, 18 cases were constructed using different student's background information. The detailed information of the cases are presented in Appendix B.

- The student background information presented to the evaluator includes *EmotionalState, PrerequisiteMastered or not,* and *StuCapability*. The description about the student's background information of the form: "This student feels confused now, his (her) learning capability index is 0.9 and the PrerequisiteMastered index is 0.9." The meaning of the term of "learning capability index" and "PrerequisiteMastered index" is introduced to each evaluator before the evaluation. The learning capability index is used to describe the student's capability of study, which can be measured by a normalization value of the average score in the school entrance exam, ranging from 0 to 1. The "PrerequisiteMastered index" can be measured by the normalized score of the prerequisite knowledge point test which ranging from 0 to 1. If there are several prerequisite knowledge points, the average score is taken. If the "PrerequisiteMastered index" equals 1, this means this student mastered the prerequisite knowledge point completely; conversely, the index value "0" means the student did not master the prerequisite knowledge point at all.

- The learning contextual information including cognitive process and the difficulty level were obtained by the analysis of the video. The emotional state and cognitive state are used as a condition to query the emotion ontology in order to generate the possible feedback tactics set. The corresponding Influence Diagram is constructed on the basis of the emotional state, cognitive state, and the possible feedback tactics set. The student's information and learning contextual information are fed into the influence diagram in order to produce the optimal feedback group. The results f2 and f1 are deduced in terms of algorithm A1 and A2 separately. Besides these two groups of results, another group of results f3, that are a less likely response, are constructed by hand. For example, the f1 is " No worry, let's review the usage of operator *." f2 is " You can handle it. Try to think it over again." , and f3 is " Wow, you got it! You are great!".
- In order to provide the evaluators with more information, the feedback tactic groups are instantiated. The feedback tactic of encouragement could be instantiated to be "You're capable of far more than you realize.", or "Try it again". The cognitive feedback tactic of "repeat" can be presented as "look at this segment again carefully please." If the cognitive feedback tactic is related to a certain knowledge point, such as the tactic of "reviewprerequisiteKP", it can be shown like "let's review the meaning of a+i. "a+i" represents the address of the element a[i] of array, and it is the same meaning with &a[0]." The detailed of the revision content are given on the basis of the context and experience.

5.2.4 Participants

Four tutors were asked to participate in the evaluation of the feedback model. There are 3 females and 1 male, aging from 33 to 51, the average age is 39.4.

5.2.5 Experimental process

Before the evaluation starts, the tutors are asked to take a short tutorial about what the terms in the description of the student background mean.

The evaluators start the evaluation. The instructional video is played from the start point and the evaluator can play the video from another point if they think it's necessary. A case list panel could help the evaluator to locate the point of a certain case. When entering a case, the evaluators will be provided with the student's background description and three pairs of instantiated cognitive and emotional feedback (fb1, fb2, fb3). The tutors will be asked to mark each of them on a scale from 1 to 5 according to how appropriate they think the feedback is in the given situation when the scenario ends. The marks could be changed during the whole evaluation process when the evaluators make a mistake.

The question presented to the evaluator is: Do you agree with this feedback?

The options are: ⊙strongly agree ⊙agree ⊙neutral ⊙disagree ⊙strongly disagree.

The evaluator submits the scores when they finish the evaluation.

5.2.6 Results and analysis

The frequency statistics are used to calculate the mean and mode satisfaction value for each feedback group. The percentage of the options including strongly agree, agree or neutral for each feedback group. Using a T-test to analyze the significance differences between fb1 and fb3, fb2 and fb3, fb1 and fb2.

Table 5-3 Frequency statistics of evaluation stage 2

		fb1	fb2	fb3
N	Valid	72	72	72
	Missing	0	0	0
Mean		4.11	3.69	2.21
Mode		5	4	2

From Table 5-3, the mean value of the satisfaction level to feedback produced by Algorithm A2 (mean fb1=4.11) is higher than the mean value of the satisfaction level of feedback produced by Algorithm A1 (mean fb2=3.69). The mode of the satisfaction level to fb2 is 5 ("strongly agree" = 5) while the mode of the satisfaction level to fb1 is 4 ("agree" = 4). On the basis of the average value and mode of the satisfaction level, the tutors are more satisfied with the feedback produced by Algorithm A2 than the feedback produced by Algorithm A1. Generally speaking, the tutors strongly agree with the feedback produced by Algorithm A2 and they agree with the feedback produced by Algorithm A1. They disagree with the feedback fb3, a less likely response, are constructed by hand. The frequency description is shown in Table 5-4. The first column lists the valid values are 1, 2, 3, 4, 5, respectively matching the options from "strongly disagree" to "strongly agree". The second column labeled "Frequency", simply reports the number of cases that fall into each category of the variable being analyzed. The third column labeled "Percent", provides a percentage of the total cases that fall into each region. The fourth column, labeled "Valid Percent," is a percentage that does not include missing cases. The last column, "Cumulative Percent", adds the percentages of each region from the top of the table to the bottom, culminating in 100%.

Table 5-4 Frequency percentage about fb1 in stage 2

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	1	1.4	1.4	1.4
	2	10	13.9	13.9	15.3
	3	3	4.2	4.2	19.4
	4	24	33.3	33.3	52.8
	5	34	47.2	47.2	100.0
	Total	72	100.0	100.0	

As to feedback produced by Algorithm 2, "strongly agree" (5) and "agree" (4) in total take up 80.5%.

Table 5-5 Frequency percentage about fb2 in stage 2

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	1	1.4	1.4	1.4
	2	8	11.1	11.1	12.5
	3	15	20.8	20.8	33.3
	4	36	50.0	50.0	83.3
	5	12	16.7	16.7	100.0
	Total	72	100.0	100.0	

As to feedback produced by Algorithm 1, "agree" (4) and " neutral " (3) totally take up 70.8%.

Table 5-6 Frequency percentage about fb3 in stage 2

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	20	27.8	27.8	27.8
	2	29	40.3	40.3	68.1
	3	12	16.7	16.7	84.7
	4	10	13.9	13.9	98.6
	5	1	1.4	1.4	100.0
	Total	72	100.0	100.0	

As to the less likely response, " neutral " (3) and "disagree" (2) totally take up 68.1%.

On the basis of the analysis about average value, mode and frequency, H0 was supported, the degree of satisfaction to the feedback based on tutor-remediation hypothesis (produced by Algorithm A2) is higher than the feedback based on self-remediation hypothesis (produced by Algorithm A1).

In addition，a t-test was performed to determine any significant differences between the three types of responses. “Significance” will be determined at $p <= 0.05$.

Table 5-7 Paired Samples Test in stage 2

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	fb1 - fb2	.417	1.275	.150	.117	.716	2.772	71	.007
Pair 2	fb1 - fb3	1.903	1.745	.206	1.493	2.313	9.250	71	.000
Pair 3	fb2 - fb3	1.486	1.565	.184	1.118	1.854	8.055	71	.000

The analysis revealed a significant difference between the feedback based on tutor-remediation hypothesis and the system’s less preferred responses ($t(71) = 9.250$, $p < 0.05$), as well as a significant difference between the feedback based on self-remediation hypothesis and the system's less preferred responses ($t(71) = 8.055$, $p < 0.05$). In addition, there was significant difference between the feedback based on tutor-remediation hypothesis and the feedback based on self-remediation hypothesis, ($t(71)= 2.772$, $p < 0.05$).

5.3 Stage 3

The joint model is the emotion analysis model and the emotion feedback model working together. The inputs are the same as in the emotion analysis model, and the outputs of the emotion analysis model are used as the inputs of the emotion feedback model. The joint model produces the feedback tactics in terms of the input to the emotion analysis model. In stage 2, the results shows that the degree of satisfaction with the feedback based on tutor-remediation hypothesis (produced by Algorithm A2) is higher than the feedback based on self-remediation hypothesis (produced by Algorithm A1), therefore, Algorithm A2 will be used in the joint model evaluation.

Figure 5-4 Evaluation page of the evaluation system in stage 3

5.3.1 Experimental hypothesis

The experiment hypotheses for evaluation in Stage 3 are proposed:

H0：The satisfaction level to the feedback combined with cognitive and emotion is higher than the satisfaction level to the feedback only using single cognitive feedback.

H1：The satisfaction level to the feedback combined with cognitive and emotion is not higher than the satisfaction level to the feedback only using single cognitive feedback.

5.3.2 Method

This evaluation method in stage 3 is the same as which is used in stage 2. The model was evaluated by 10 experienced C-programming tutors. The same evaluation platform was adapted which was used in stage 2. Each tutor was presented with the same cases. The evaluation data, participants and evaluation process are described in detail as follows.

5.3.3 Evaluation Data

The same instructional video was selected that is used in the emotion feedback model. A total of 18 cases are used in this evaluation too. In contrast with the cases that are used in stage 2, the cases that are used in the joint model, the specified emotional states are not provided, only the positive or negative states are presented to the evaluator. Each case consists of a video clip, student's background information constructed by hand, and corresponding three types of feedback. The feedback tactics are also be instantiated like in stage 2. For example, the feedback tactic of encouragement could be instantiated to be “You’re capable of far more than you realize.” The three types of feedback tactics respectively are: the feedback combined with cognitive and emotional feedback (fb1), only the cognitive feedback (fb2), and feedback (fb3), that are a less likely response, are constructed by hand.

5.3.4 Participants

Ten tutors were asked to participate in the evaluation of the feedback model. There were 6 females and 4 males, aging from 33 to 51, the average age is 39.4.

5.3.5 Experimental process

1) Before the evaluation started, the tutors were asked to undertake a short tutorial about what the terms in the description of the student background mean.
2) The evaluators start the evaluation. The instructional video was played from the start point. The evaluator can play the video from any point they judge to be appropriate. A case list panel is used to help the evaluator to locate the point to a certain case. When entering a case, the evaluators are provided with the student’s background description and three groups of instantiated feedback (fb1, fb2, fb3). The tutors were asked to mark each of them on a scale from 1 to 5 according to how appropriate they thought the feedback was in the given situation when the scenario ends. The marks could be modified during the whole evaluation process if the evaluator thinks their marks are not appropriate.

3) The question presented to the evaluator is: How do you agree with this feedback? The options are: ⊙strongly agree ⊙agree ⊙neutral ⊙disagree ⊙strongly disagree.

4) The evaluator submits the marks when they finish the evaluation. When the evaluation is finished, the evaluator cannot change the marks.

5.3.6 Results and analysis

The statistical techniques adopted in stage 3 are the same with the techniques adopted in stage 2. For each feedback group, as to the satisfaction level score, the frequencies statistics was used to attain the mean value, and mode etc. T-test was used to analyze the significance differences between fb1 and fb3, fb2 and fb3, fb1 and fb2.

Table 5-8 Frequency Statistics of evaluation stage 3

		fb1	fb2	fb3
N	Valid	180	180	180
	Missing	0	0	0
Mean		4.31	3.94	2.36
Mode		5	4	2

From Table 5-8, the mean value of the satisfaction level to feedback which is combined with cognitive and emotional feedback (mean fb1=4.31) is higher than the mean value of the satisfaction level to feedback which only includes cognitive feedback (mean fb2=3.94). The mode of the satisfaction level to fb1 is 5 ("strongly agree" = 5) while the mode of the satisfaction level to fb2 is 4 ("agree" = 4). On the basis of the average value and mode of the satisfaction level, the tutors are more satisfied with the combined cognitive and emotional feedback than sole cognitive feedback. Generally speaking, the tutors strongly agree with the combined cognitive and emotional feedback and they agree with the sole cognitive feedback. They disagree with the feedback fb3, a less likely response, are constructed by hand. The frequency description is showed below.

Table 5-9 Frequency percentage to fb1 in stage 3

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	1	.6	.6	.6
	2	9	5.0	5.0	5.6
	3	19	10.6	10.6	16.1
	4	56	31.1	31.1	47.2
	5	95	52.8	52.8	100.0
	Total	180	100.0	100.0	

As to feedback combined with cognitive feedback and emotional feedback, "strongly agree" (5) take up 52.8%.

Table 5-10 Frequency percentage to fb2 in stage 3

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	2	14	7.8	7.8	7.8
	3	19	10.6	10.6	18.3
	4	111	61.7	61.7	80.0
	5	36	20.0	20.0	100.0
	Total	180	100.0	100.0	

As to feedback which only includes cognitive feedback, "agree" (4) totally take up 61.7%.

Table 5-11 Frequency percentage to fb3 in stage 3

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	54	30.0	30.0	30.0
	2	56	31.1	31.1	61.1
	3	33	18.3	18.3	79.4
	4	26	14.4	14.4	93.9
	5	11	6.1	6.1	100.0
	Total	180	100.0	100.0	

As to the less likely response, "strongly disagree " (1) and "disagree" (2) totally take up 61.1%.

On the basis of the analysis about average value, mode and frequency, H0 was supported, The satisfaction level with the feedback when the cognitive and emotional aspects are combined is higher than the satisfaction level with cognitive feedback.

In addition，a t-test was performed to determine any significant differences between the three types of responses. “Significance” is determined at $p <= 0.05$.

Table 5-12 Paired Samples Test in stage 3

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference Lower	Upper			
Pair 1	fb1 - fb2	.367	.769	.057	.254	.480	6.399	179	.000
Pair 2	fb1 - fb3	1.950	1.819	.136	1.682	2.218	14.379	179	.000
Pair 3	fb2 - fb3	1.583	1.644	.123	1.342	1.825	12.922	179	.000

The analysis revealed a significant difference between the feedback combined with cognitive feedback & emotional feedback and the system’s less preferred responses ($t(179) = 14.379$, $p < 0.05$), as well as a significant difference between the feedback only includes cognitive feedback and the system’s less preferred responses ($t(179) =$

12.922, $p < 0.05$). In addition, there was significant difference between the feedback combined with cognitive feedback & emotional feedback and the feedback only includes cognitive feedback, ($t(179)= 6.399$, $p < 0.05$).

5.4 Summary

This chapter presented the evaluation study on the emotion analysis model and emotion feedback model, including methodology and evaluation process. The evaluation consist of three stages – Stage1: Evaluation of the emotion analysis model; Stage 2: Evaluation of the emotion feedback model; Stage 3: The evaluation of the two models combined. In stage 1, H0 was supported. The emotion analysis model can be used to classify negative emotion and hence deduce the learner’s cognitive state. Evaluation to the emotion analysis model showed that the Bayesian network classifies the emotion state with 60% accuracy and classifies both the emotion and cognitive state with 48.82% accuracy. In stage 2, H0 was supported. The degree of satisfaction to the feedback based on tutor-remediation hypothesis (produced by Algorithm A2) is higher than the feedback based on self-remediation hypothesis (produced by Algorithm A1). In stage 3, H0 was supported. The satisfaction level with the feedback when the cognitive and emotional aspects are combined is higher than the satisfaction level with cognitive feedback.

Chapter 6

Discussion

In this chapter we discuss all that has been presented so far in this thesis. The discussion falls into three sections, matching Chapters 3 to 5 respectively: the video study of human tutors from Chapter 3; the emotion analysis model and feedback model from Chapter 4; the evaluation from Chapter 5. These chapters will now be discussed in turn.

6.1 The video study

There were two video studies implemented to investigate the characteristics of two types of interactions in learning: non-interactive environments and interactive environments. In the former one, the students learn by themselves via watching an instructional video, and in the latter the students were taught by a human tutor. The aims of these studies were to gather data to construct the emotion understanding and feedback models.

Next, we discuss five aspects from the video study of human tutors that was presented in Chapter 3: learning content, subjects, settings, the amount of data, and improvements that could be made to the coding scheme.

6.1.1 Learning content

The module selected in the video study is C programming. The content for session 1 was material on computer main memory storage using an array. This was relatively basic and included topics such as array declaration, initialization and usage. The content for session 2 was more advanced and explained how pointers could be used to operate on elements in an array. The different difficulty level can induce different emotional states. In addition, the study of a programming language might induce more negative emotional states than in learning the courses like history or culture. The parameters in the emotion analysis model are learned from the cases on the basis of the study of C programming in the video study, so the Bayesian Network will need learning parameters to be collected in the corresponding domain if generalized to different domains. The feedback tactics, for example review related prerequisite Knowledge point, can be generalized to different domain.

C-programming can be categorized as complex learning. Complex learning requires learners to generate inferences, answer causal questions, diagnose and solve problems, make conceptual comparisons, generate coherent explanations, and demonstrate application and transfer of acquired knowledge(Graesser et al., 2010). This form of learning can be contrasted with shallow learning activities (memorizing key phrases and facts) and procedural learning. Complex learning is inevitably accompanied with block by failure, so the learner experiences a host of affective states(D’Mello et al., 2012). So, the results in this study need to be evaluated before generalized to shallow learning forms.

6.1.2 Subjects in the video study

The student participants in the video study are first year students in the university. If the learners are students in primary school or middle school, the categories and frequencies of appeared emotional states might be different. In addition, the major of the students might affect the motivation to the study. In the video study, in the non-interactive and the interactive settings, the major of the students respectively are physics and computer science. C programming is a core course in the major of computer science, so the students majoring in computer science might treat this course more positively. Generally speaking, the students majoring in physics might have lower motivation towards C programming than the students majoring in computer science.

The lecturers in the video study have effects on the results as well. Many aspects of the lecturers, such as the characteristic, expressive style, the instructional method and etc., may cause different emotional states and cognitive states of students, and may affect the way in which they respond to the students.

6.1.3 Settings

In the non-interactive environment, the students were not allowed to control the play of the instructional video during the learning process. This design may result in the students exhibiting more negative states when they are watching the videos. This restrictive condition can, however, help to achieve the video synchronization in the data processing stage. In any case, normally the students cannot control the procedure during a classroom lecture, so this setting is reasonable when the experiment design mimics the learning environment in classroom.

6.1.4 Is there enough data?

"Quick and Dirty Ethnography" was used in the data collecting stage, so the amount of data collected was not large. In the observation of the non-interactive environment, we obtained 10 student's video files with a complete duration of 310 minutes. In the observation of the interactive environment, we obtained 10 student’s video files totaling around 375 minutes length for session 3 and session 4. Stimulated recall collected 267 annotations (0.71 emotional state change per minute) from the students and 106 annotations (2.83 annotations per minute) from the lecturers. The minimum number and the maximum number of annotations student reported respectively are 11 and 65. This difference in the number is caused by the difference of the students' ability to perceive their emotional states. The data amount is not large, but it is enough to build the models in the research. Ideally, more data could be used to improve the models and train the parameters better, and more feedback tactics can be extracted.

6.1.5 Improvements to the coding scheme

Specific characteristics of the students are not taken into account in the experimental design because normally the lecturers did not know the student's characteristic in real classroom teaching but they still can apply suitable feedback. Without considering the students' characteristic, the complexity of the models can be simplified. Clearly, if the student's characteristic is considered, the feedback can be offered more personalized and more effective.

In addition, the student's gender should be considered in order to offer better response, because girls are known to be more frustrated if they do not receive both task and affect based support (Woolf et al., 2007).

The intensity of the student's emotional state is not incorporated into the experimental design because the categorized representation model was adopted. If the intensity of an emotional state increased to some degree, it will be changed into another category. For example, the intensity of confusion increases to a certain degree, the emotional state turns into frustration. If intensity of an emotional state needs be represented, such as "very confused", "normal confusion", the correspondingly more sophisticated emotion recognition techniques are needed. This could not be achieved through the use of the web camera and software in our study.

In the data processing stage, there are two extra factors which should be considered in the coding scheme. One is whether the student is on task or not concentrating. On the basis of the student's self report, sometimes their minds wandered during learning, but they appear to be immersed in a flow state in the corresponding time in the videos. The absent state tends to appear especially in self learning by video, so these two totally opposite states should be distinguished. Another factor is the student's major. The student's motivation could be different even to the same course due to their different majors. For example, a student majoring in computing science normally shows more motivation in programming than the students majoring in other fields.

This conclusion is obtained by teachers' experience and not be reflected in the background study directly. Due to the different majors, the requirements of the students are different as well, so the feedback should be different. The students majoring in computing science should get deeper responses than the students in other majors.

6.2 Emotion analysis model and emotion feedback model

We constructed two emotional models in the research in order to understand the learner's emotional states and provide them appropriate feedback, one is the emotion analysis model which is used to analyse the specific emotional state and the cognitive state that causes the emotional state, and the other is feedback model which is used to select the appropriate feedback tactics for the learner.

Here, we discuss four issues in the design of the emotion analysis model and emotion feedback model.

6.2.1 The feasibility of using eye blink to determine emotional state

The design of the emotion analysis model relies on the feasibility of using eye blink to determine emotional state. In Chapter 3.4.2, we discussed how to obtain an individual blink frequency threshold value by watching a benchmark film, and this threshold value can be used to estimate which type of emotional states, negative or positive, the students are in. Besides the blink frequency, some other eye-related features also can be considered in the emotion analysis model, such as the duration of each blink, the duration between continuous two blinks, the blink numbers in a certain time length, etc. These features could be used to determine students' emotional state and make it more robust and reliable.

6.2.2 Integrating facial expression recognition technique

The results in the background study show that the students' facial expression and body movement are not frequent during their learning process. This may be caused by the instructional content, lecturer's teaching style, however, other research suggests that movement is important and does occur. Even these changes are few, once they appear, these obvious features and activities are normally related to strong emotional states. The facial expression recognition technique, including simple body movement (forward and backward), are mature and unobtrusive, and can be realized by web camera and software. For example, the emotion tool released by Microsoft can be used to create systems that recognize eight core emotional states – anger, contempt, fear, disgust, happiness, neutral, sadness or surprise – based on universal facial expressions that reflect those feelings (Linn, 2015). These techniques could be added in the emotional analysis model to make it to recognize learner's emotional state whatever their facial expression is obvious or not.

6.2.3 Improvements to the affective learning ontology

The affective learning ontology is constructed on the basis of the background video study which mimics classroom lecture environment. Therefore the ontology has limitations in the forms of learning, feedback tactics and student's characteristics. The affective learning ontology could be improved in these aspects:

- The forms of learning. Besides the form of lecture, other forms could be considered in the ontology, such as discussion, practice activity, test, game, etc.
- The feedback tactics. Some feedback tactics fitting the on-line learning can be added into the ontology to extend the range of feedback tactics, such as providing keywords for searching, providing the links of learning resources, blocking the messages from the chat tool, joining the discussion group, posting questions on the BBS, etc.
- Student's characteristics. Student's characteristics could be described in this ontology in detail. The relationships between student's characteristic and their emotional states, between student's characteristic and the feedback tactics are not described in this ontology.

Except for these aspects above, the affective learning ontology can be related to the existed domain knowledge ontology. For example, the existing domain knowledge ontology described the knowledge points and the relationship among the knowledge points, so, these concepts and relationship should be related to the "KD point" and the feedback tactic of "review ReviewPrerequisiteKP" in the affective learning ontology.

6.2.4 Improvements to the influence diagram model

The influence diagram model is used to select the optimal feedback tactic pairing group. The construction of the model took a number of factors in account, which includes "CognitiveState", "EmotionalState", "StuCapability", "KPDifficulty" and "PrerequisiteMastered", "CognitiveCost", "CognitiveUtility", "AffectiveCost", "AffectiveUtility". More factors could be considered in order to produce more personalized feedback, for example, the learner's characteristic, gender, etc. Research indicated that gender differences were obtained with girls showing stronger outcomes when presented with affect-support interventions and boys with task-support interventions (Picard and Burleson, 2006).

The cost of each cognitive feedback tactic and affective feedback tactic, and the produced utility were given on the basis of experience in this research. These values need to be adjusted in practice.

The learners are expected to gain knowledge and skills with an accompanying pleasant experience, but in learning, especially deep learning, the negative emotional states such as confusion are unavoidable. So further research work is needed to study how to keep the learner at the limits of their comfort zone and gain maximum learning utility at the same time.

When the system should offer feedback to the learners also needs to be considered. Immediate feedback is not necessary at all the time, sometimes it causes the learners' discomfort.

6.3 The Evaluation results

6.3.1 Discussion to the evaluation results in stage 1

The aim of evaluation stage 1 is to evaluate the emotion analysis model. The goal of the emotion analysis model is to classify the negative emotion into specified emotional state and can be used to deduce the learner's cognitive state. Evaluation to the model showed that the Bayesian network classifies the emotional state with 60% accuracy and classifies both the emotional and cognitive state with 48.82% accuracy. A random selection would be respectively are 33.3% and 16.7% accurate.

The evaluation in (Sabourin et al., 2011b) used the same method and showed that the Bayesian network could classify seven emotional states with 25.5% accuracy and could classify the valence of the emotional state, namely positive or negative states, with 66.8% accuracy. Sabourin also used a Dynamic Bayesian network and was able to classify seven emotional state with 32.6% accuracy and valence with 72.6% accuracy. D'Mello and Graesser (2009) achieved accuracies of classifying emotional states between two, three and four affective states were 71%, 55% and 46%. The accuracy rates are summarized in Table 6-1. The column labeled with "Accuracy rate by random selection" means the accuracy rate by selecting a state by chance.

Table 6-1 Accuracy rate comparison

Research work	Accuracy rate	Accuracy rate by random selection	States to identify	Technique
Sabourin et al. (2011b)	66.8% 72.6%	50%	valence (positive or negative states)	BBN DBN
	25.5% 32.6%	14.29%	seven affective states	BBN DBN
D'Mello and Graesser (2009)	71% 55% 46%	50% 33.3% 25%	two affective states three affective states four affective states	Machine learning algorithms *
This research	60%	33.3%	three affective states	BBN
	48.82%	16.7%	three affective states plus one cognitive state	BBN

**including Bayesian, Functions, Instance Based Classifiers, Rule, Decision Tree*

D'Mello and Graesser (2009) detected learners' affect by monitoring their body position and arousal during interactions with an Intelligent Tutoring System. Training and validation data on affective states were collected in a learning session with the ITS. Various standard classification techniques were used in detecting affect from posture related feature. Sabourin et al. (2011b) developed learner's emotional states predictive models by modeling cognitive appraisal process. Predictive models are empirically learned from data acquired from interacting with the game-based learning environment. The parameters were learned using the EM algorithm and the model was trained using 10-fold cross-validation. The learning environment in D'Mello's research and our research both are a learning session, while Sabourin's research is game-based learning environment. Sabourin's research adopts similar methodology as our research, both modeling cognitive appraisal process by Bayesian network. These three studies achieved similar emotional state recogniton accuracy rates under the same states number. For two states, the accuracy rates in (Sabourin et al., 2011b) are 66.8% and 72.6% respectively using BN and DBN, whilst the accuracy rates in (D'Mello and Graesser, 2009) is 71%. For three and four states, the accuracy rates in () is 55% and 46%, and the accuracy rates in our research is 60% and 48.82%.

Sabourin et al. (2011) achieved better accuracy by considering the emotional states transition using DBN than without considering the emotional states transition using BN in their own work. D’Mello and Graesser (2012) proposed a hypothesis to illustrate the transition among the states of confusion, frustration and boredom in deep learning. The confusion state occurs due to cognition disequilibrium, and transits to the frustration state when the student experiences failure. Persistent frustration may also transition into boredom. Adding this hypothesis in to the emotion analysis model could help to categorize the negative emotional states. In our research, the modeling of the emotion analysis model mainly considers the causal relathionship between the cognitive state and emotional state, and is implemented by Bayesian belief network. The inconsistency of state recognition in our experiment mainly appears in the cases that the student reported they were in frustration while the network inferred that they were in confusion. The model can distinguish frustration from confusion in the event of providing feedback, but cannot achieve this in other situations. Our motion analysis model has answered the research question of what causes such emotional states in a learning environment and how to implement the analysis process by use of a computational model. If considering the transition among the states in the emotion analysis model and modeling this by DBN might produce better results. This could be realized by adding a time slot at time t_i and add the links between the nodes in t_i to the nodes in t_{i+1}. Although this would require further research to ascertain if the results could be generalized.

The state of boredom may be caused by learning content which is either too complex or too simple. The boredom state caused by too simple content can be inferred by the Bayesian network in the emotion analysis model with a "successful" cognitive state. But if the emotional state is caused by content which is too complex, it tends to be categorized to "confusion" state with a "failed" cognitive state in the Bayesian network. Although the inferred emotional state is inconsistent, the correct inferred cognitive state can ensure that the cognitive feedback is appropriate.

The discussion of the evaluation of emotion analysis model only includes the classification to the negative emotional states, and this is on the basis of the accurate classification by the blink frequency. Using eye-related features to deduce whether the emotional state is positive or negative still needs further research work. The positive emotional states are not classified further in this research because the positive emotional states are mapped to the same cognitive state and have the same feedback tactics according to the results in observation study. In the evaluation, the feedback tactic to the positive emotional states was selected randomly from the applicative feedback tactics. The application of the optimal feedback tactic to the positive emotional state needs further study.

6.3.2 Discussion of the evaluation results in stage 2

The aim of stage2 is to evaluate the emotion feedback model. The goal of the emotion feedback model is to produce the most appropriate cognitive and emotional feedback tactics pairing group to the student. The evaluation results support the belief that the degree of satisfaction to the feedback based on tutor-remediation hypothesis (produced by Algorithm A2) is higher than the feedback based on self-remediation hypothesis (produced by Algorithm A1).

The evaluators in state 2 are experienced teachers, so it is reasonable that the feedback based on tutor-remediation hypothesis was supported. If the evaluators are students, the results might be different depending on the characteristics of the students.

6.3.3 Discussion to the evaluation results in stage 3

In evaluation stage 3, the emotion analysis model and the emotion feedback model work together, and the results show that the tutors are more satisfied with the combined cognitive and emotional feedback than sole cognitive feedback.

The evaluation design of stage 3, only considers the teachers' subjective feeling to the feedback in the affective learning system, but does not involve the students. The students' subjective feeling and learning gain should be taken into account. The students' subjective feeling could be acquired by questionnaire. And their learning gains could be measured by pretest and posttest, or by a group using cognitive and emotional feedback and a group only using cognitive feedback.

6.3.4 Summary

This chapter discussed the video study of human tutors from Chapter 3, the emotion analysis model and feedback model from Chapter 4 and the evaluation from Chapter 5. In the discussion of the video study, problems were discussed including learning content, subjects, settings, the amount of data, and improvements that could be made to the coding scheme. In the discussion of the emotional models, four issues were discussed in the design of the emotion analysis model and emotion feedback model, including the feasibility of using eye blink to determine emotional state, integrating facial expression recognition technique to determine emotional state, improvements to the affective learning ontology, and improvements to the influence diagram model. In the discussion of the evaluation results, the evaluation results in stage 1, 2 and 3 were discussed respectively. In the discussion of the evaluation results in stage 1, accuracy rate of classifying the emotional state and cognitive state in the emotion analysis model in this research were compared with other research. The inconsistency of the results was discussed and it was found that the transition among the states could be considered in the emotion analysis model to improve the classify accuracy. The discussion of the evaluation results in stage 2 and 3 analysed the reason why the results appear and indicated that the students should be involved in the evaluation in the future.

Chapter 7

Conclusion

In chapter 7, the research questions set out in chapter 1 will be addressed, the contributions of this research will be presented and potential future research which extends the work described in this thesis will be proposed.

7.1 Answers to the research questions

There are three research questions set out in chapter 1.

- Question 1: Which emotions are most important to a learner in learning and how to represent these emotional states?
- Question 2: What causes such emotional states in a learning environment and how to implement the analysis process by use of a computing model?
- Question 3: How to use a computing model to generate the feedback to the learners in terms of their cognitive and affective states?

Question 1 was answered in theory by literature research in Chapter 2 and experimentally via stimulated recall of the students in the video study in Chapter 3. On the basis of the statistical analysis of the words describing emotion which appear in the literature, it was found that six emotional states were candidates for being most important to a learner when learning. The emotional states set comprises: {boredom, frustration, confusion, flow, happiness, interest}. Those emotional states were subsequently examined in the video study. The learners were asked to map the emotions they experienced during the learning process to the states identified by the literature research. The result shows that the emotional states in the emotion set we defined were sufficient for 99% of the cases studied. Further, emotional states {happy, interest, flow} are classified into positive emotional state and {boredom, confusion, frustration} are classified into negative emotional state.

Question 2 was answered by the video study in Chapter 3 and the emotion analysis model in Chapter 4. The students were asked to describe the causes of their emotional states. The main causes for each emotional state were summarized in Table 3.3. Student's information (age, major, blink frequency, body movements, emotional states, the causes of the emotional state, etc.) and the learning process (learning content, instructional step, the time lasted , etc.) were collected in the video study and much of this information was utilized to construct the emotion analysis model by Bayesian belief network. The construction of the emotion analysis model was described in section 4.4 and the evaluation of the emotional analysis model was described in section 5.1.

Question 3 was answered by the video study in Chapter 3 and the emotion feedback model in Chapter 4. The teachers were asked to describe their teaching activities and why they selected a certain teaching activity. Teachers' interpretations of the causes of their activities during teaching were summarized in table 3.4. The information extracted from the video study including student's information, the teaching-learning procedure, the instructional material, etc. are utilized to construct the emotion feedback model which embraces an affective learning ontology and an influence diagram model. The affective learning ontology model is used to represent the concepts and relationships in the affect learning environment. And the emotion feedback selection model was constructed by influence diagram modeling technique. The detailed constructing process of the emotion feedback model was described in section 4.5 and the evaluation of emotion feedback model was described in section 5.2.

7.2 Research Contributions

This research is on the basis of the learning form in which students learn by watching instructional video. The contributions that this thesis makes are summarized below:

(1) Two video studies were designed and carried out to investigate the characteristics of two types of interactions in learning: non-interactive environments and interactive environments.

- Instead of a large scale study, the methodology "Quick and Dirty Ethnography" was adopted to see how emotion works in learning generally. This approach is capable of providing much valuable knowledge in an affective learning environment setting in a relatively short space of time. In total 15 students, 2 tutors, 4 sessions participated in the video studies. Twenty student's video files totaling around 685 minutes length, 4 lecture video files around 139 minutes length were collected and analyzed.

- It was found that six emotional states, including boredom, frustration, confusion, flow, happiness, interest, were identified as being the most important to a learner when learning.

- The blink frequencies can be used to classify the emotional states into positive or negative state. Blink frequencies during learning were associated with the learner's emotional state and were mainly affected by three factors, the difficulty level of the knowledge point, the task types, and the individual.

- It is necessary to intervene when students are in self-learning through watching instructional video in order to ensure that attention levels do not continue to decrease. For an e-learning system, the ability to vary a presentation depending on the recipient's reaction to it is therefore important. In the video study, the overall tendency of the blink curve in self-learning experiments decreased gradually. In contrast, the blink curves produced in both sessions of interactive learning with a human tutor did not show a declining tendency, but show an increasing tendency. So, simply making video material available is not as good as taught sessions.

- The data collected in the video study are the basis of the construction of the emotion analysis model and emotion feedback model. In the stimulated recall stage, the students were asked to describe the causes of their emotional states and the tutors were asked to recall and describe their teaching activities and why they selected a certain teaching activity. The main causes for each emotional state of students in learning were summarized in Table 3-3. Teachers' interpretations about the causes of their activities during teaching were summarized in Table 3-4.

(2) A novel emotion analysis model was constructed as part of an affective learning system.

- In the emotion analysis model, a novel method was proposed to classify the emotion into positive or negative state using the eye blink frequency. The system determines the student's emotional state by blink frequency. If it is negative, the emotion analysis model attempts to reason what emotional state the student is in and why by using the student's background information and learning contextual information.
- A novel Bayesian belief network (BBN) model was constructed to determine the student's cognitive and emotional state while watching an instructional video. The construction of the BBN model was on the basis of the data collected in the video study and Gagne's theory (1965) in the field of education. The conditional probability table was determined by the data in the video study and Expectation Maximization (EM) parameter learning algorithm (Lauritzen, 1995).
- Evaluation results showed that the Bayesian network classifies the emotion state with 60% accuracy and classifies both the emotion and cognitive state with 48.82% accuracy. With respect to discriminations between three affective states, the research achieves 60% accuracy, a higher rate than in D'Mello and Graesser (2009) which has the accuracy rate of 55%. The detailed comparison of accuracy rates in different research work were presented in Table 6-1.

(3) A novel method for producing appropriate feedback tactics in affective learning system was developed by Ontology and an Influence diagram (ID) approach, using the information extracted from the video study.

- The ID model is used to select appropriate cognitive and emotional feedback tactics in term of the student's current cognitive and emotional state using utility analysis. Considering the affective feedback has impact on Affective State and Cognitive State in next time slot, this model splits affective feedback and cognitive feedback into two time slots respectively and affective feedback is given prior to cognitive feedback.
- On the basis of the tutor-remediation hypothesis and the self-remediation hypothesis, two algorithms were designed on the basis of the ID model. Algorithm A1 is based on tutor-remediation hypothesis and Algorithm A2 is based on tutor-remediation hypothesis.
- The evaluation results show that the degree of satisfaction with the feedback based on the tutor-remediation hypothesis is higher than the feedback based on self-remediation hypothesis. And the tutors are more satisfied with the combined cognitive and emotional feedback than cognitive feedback on its own.

Overall the thesis demonstrates that there is a difference between classroom learning and video study and then sets out techniques for reducing this difference. The recommended methodology and techniques in the context of this project that reduce this difference are: “Quick and Dirty Ethnography” methodology, Bayesian belief network, Ontology and an Influence diagram (ID). “Quick and Dirty Ethnography” is capable of providing much valuable knowledge in an affective learning environment setting in a relatively short space of time. The Bayesian Belief Network technique is suitable for dealing emotional problems with uncertainty and complexity and can represent the causal relationship between the cognitive state and emotional state. An ontology technique is suitable for specifying the terms and relations in an affective learning environment, and querying the possible cognitive feedback tactics and affective feedback tactics. The influence diagram technique has a causal and uncertainty representation structure which provides powerful capabilities in handling complex situations and incorporates the evolution of user affect and the temporal aspect of decision making with the dynamic structure.

7.3 Future Work

This research work could proceed from the aspects below in the future:

1) Improving the emotional analysis model with the emotional states transition. The current emotional analysis model only takes account of the factors such as instructional material, instructional process, learner's cognitive state, etc., but without the emotional state on the last moment. The hypothesis about the transition among the states of confusion, frustration and boredom in deep learning (D’Mello and Graesser, 2012) can be applied into the emotion analysis model. For example, the confusion state transits to the frustration state when the student experiences failure, persistent frustration transits into boredom. The system's incorrect classification about the

confusion and frustration, the frustration and boredom, would be decreased with adding the consideration of the emotional states transition. This could be realized by adding a time slot in time t_i and add a link between the nodes in t_i to the nodes in t_{i+1}. It might improve the accuracy rate of classification by considearing emotional states transition.

2) Improving the emotion feedback model by taking the learners' personality and gender account in. Robison et al. (2010) indicated that student personality profiles can serve as a powerful tool for informing affective feedback models. Picard and Burleson (2006) indicated that girls show stronger outcomes when presented with affect-support interventions and boys with task-support interventions. Adding these two factors in the emotional feedback model will make it to produce more personalized feedback.

3) Improving the evaluation with the students as evaluators and using the results to revise the emotion models. Only experienced teachers were used to evaluate the emotion models of the system in this research, this is not sufficient. The students' subjective feeling and learning gain should be taken into account. The students' subjective feeling could be acquired by questionnaire, and their learning gains could be measured by pretest and posttest. These evaluation results could be used to improve the parameters in the feedback model, such as the cost and utility values, which were set by experience.

4) In the evaluation state, the feedback tactics were instantiated by hand, and the

feedback were presented by text description. The presentation of the feedback has straight impact to the feedback effect. So, further research will focus on how to instantiate the feedback tactic to the specific feedback, including by words, tone of emotional feedback, the agent's facial expression and body language. And how to induce the students' positive emotional states and relieve their negative emotional states by external skills, such as deep breathing, body exercises, etc.

7.4 Summary

This chapter answered the research questions set out in chapter 1, concluded the contributions of this research and proposed potential future research which extends the work described in this thesis.

Landowska (2014) indicated that affective computing grew up from infancy, however it is still far from maturity especially when applied to learning support. During a decade of diverse investigations, affective-cognitive imbalance in ITS has shown some advances, however this has not been reflected in learning support tools. This thesis investigated how to enhance ITS by responding to affective states, including how to understand the emotional state of students and how to select an appropriate feedback tactic for the students in affective learning environment. An emotion analysis model and an emotional feedback tactics selection model was designed and developed. These models were evaluated by the data extracted from the video study and experienced tutor respectively. Future work should focus on evaluating the models in more learning scenarios with the aim to refine the models to produce a practical form of learning support tool.

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Appendix A The affective learning Ontology


```
<?xml version="1.0"?>


<!DOCTYPE rdf:RDF [
    <!ENTITY owl "http://www.w3.org/2002/07/owl#" >
    <!ENTITY xsd "http://www.w3.org/2001/XMLSchema#" >
    <!ENTITY owl2xml "http://www.w3.org/2006/12/owl2-xml#" >
    <!ENTITY rdfs "http://www.w3.org/2000/01/rdf-schema#" >
    <!ENTITY rdf "http://www.w3.org/1999/02/22-rdf-syntax-ns#" >
    <!ENTITY                                        EmotionOntology
"http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#" >
]>


<rdf:RDF
xmlns="http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#"

xml:base="http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.ow
l"
     xmlns:rdfs="http://www.w3.org/2000/01/rdf-schema#"
     xmlns:owl2xml="http://www.w3.org/2006/12/owl2-xml#"
     xmlns:owl="http://www.w3.org/2002/07/owl#"
     xmlns:xsd="http://www.w3.org/2001/XMLSchema#"
     xmlns:rdf="http://www.w3.org/1999/02/22-rdf-syntax-ns#"

xmlns:EmotionOntology="http://www.owl-ontologies.com/marine.owl/2011/11/Emot
ionOntology.owl#">
    <owl:Ontology
rdf:about="http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.ow
l"/>



    <!--
    ///////////////////////////////////////////////////////////////////////////////////////
    //
    // Object Properties
    //
    ///////////////////////////////////////////////////////////////////////////////////////
     -->
```

```
<!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#canbeUse
dinCog -->

<owl:ObjectProperty rdf:about="&EmotionOntology;canbeUsedinCog">
    <rdfs:comment>可被用于**认知/情感状态的认知反馈策略
</rdfs:comment>
    <owl:inverseOf
rdf:resource="&EmotionOntology;hasCognitiveFeedbackTactic"/>
</owl:ObjectProperty>



<!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#canbeUse
dinEmo -->

<owl:ObjectProperty rdf:about="&EmotionOntology;canbeUsedinEmo">
    <rdfs:comment>可被用于**认知/情感状态的情感反馈策略
</rdfs:comment>
    <owl:inverseOf
rdf:resource="&EmotionOntology;hasEmotionalFeedbackTactic"/>
</owl:ObjectProperty>



<!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#hasCogni
tiveFeedbackTactic -->

<owl:ObjectProperty
rdf:about="&EmotionOntology;hasCognitiveFeedbackTactic">
    <rdfs:comment>可用认知反馈策略</rdfs:comment>
    <rdfs:range rdf:resource="&EmotionOntology;CognitiveFeedbackTactic"/>
</owl:ObjectProperty>



<!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#hasEmoti
onalFeedbackTactic -->
```

```
    <owl:ObjectProperty
rdf:about="&EmotionOntology;hasEmotionalFeedbackTactic">
        <rdfs:comment>可用情感反馈策略</rdfs:comment>
        <rdfs:range
rdf:resource="&EmotionOntology;EmotionalFeedbackTactic"/>
    </owl:ObjectProperty>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#isAssocia
tedwith -->

    <owl:ObjectProperty rdf:about="&EmotionOntology;isAssociatedwith">
        <rdfs:comment>**认知状态会与**情感状态相关，及**认知过程中会出
现**情感状态</rdfs:comment>
        <rdfs:domain rdf:resource="&EmotionOntology;CognitiveState"/>
        <rdfs:range rdf:resource="&EmotionOntology;EmotionalState"/>
    </owl:ObjectProperty>



    <!--
    ///////////////////////////////////////////////////////////////////////////////////////
    //
    // Data properties
    //
    ///////////////////////////////////////////////////////////////////////////////////////
     -->




    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#hasIntens
ityValue -->

    <owl:DatatypeProperty rdf:about="&EmotionOntology;hasIntensityValue"/>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#hasText
```

```
-->

        <owl:DatatypeProperty rdf:about="&EmotionOntology;hasText">
                <rdfs:range rdf:resource="&xsd;string"/>
                <rdfs:domain rdf:resource="&owl;Thing"/>
        </owl:DatatypeProperty>



        <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#hasTime
Length -->

        <owl:DatatypeProperty rdf:about="&EmotionOntology;hasTimeLength">
                <rdfs:domain rdf:resource="&EmotionOntology;Pause"/>
        </owl:DatatypeProperty>



        <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#hasValue
-->

        <owl:DatatypeProperty rdf:about="&EmotionOntology;hasValue">
                <rdfs:range rdf:resource="&xsd;string"/>
        </owl:DatatypeProperty>



        <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#hasVideo
Address -->

        <owl:DatatypeProperty rdf:about="&EmotionOntology;hasVideoAddress"/>



        <!--
        ///////////////////////////////////////////////////////////////////////////////////////
        //
        // Classes
        //
        ///////////////////////////////////////////////////////////////////////////////////////
          -->
```

```
    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Acceptan
ce -->

    <owl:Class rdf:about="&EmotionOntology;Acceptance">
        <rdfs:subClassOf
rdf:resource="&EmotionOntology;PositiveEmotionsFeedback"/>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Anticipat
ing -->

    <owl:Class rdf:about="&EmotionOntology;Anticipating">
        <rdfs:subClassOf rdf:resource="&EmotionOntology;CognitiveState"/>
        <rdfs:comment>informing learners of the objective</rdfs:comment>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Boredom
-->

    <owl:Class rdf:about="&EmotionOntology;Boredom">
        <rdfs:subClassOf rdf:resource="&EmotionOntology;NegativeEmotion"/>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Cognitiv
eFeedbackTactic -->

    <owl:Class rdf:about="&EmotionOntology;CognitiveFeedbackTactic"/>
```

```
    <!-- http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#CognitiveState -->

    <owl:Class rdf:about="&EmotionOntology;CognitiveState"/>



    <!-- http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Confusion -->

    <owl:Class rdf:about="&EmotionOntology;Confusion">
        <rdfs:subClassOf rdf:resource="&EmotionOntology;NegativeEmotion"/>
    </owl:Class>



    <!-- http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Congratulation -->

    <owl:Class rdf:about="&EmotionOntology;Congratulation">
        <rdfs:subClassOf rdf:resource="&EmotionOntology;PositiveEmotionsFeedback"/>
    </owl:Class>



    <!-- http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#ControlOfNegativeEmotionsFeedback -->

    <owl:Class rdf:about="&EmotionOntology;ControlOfNegativeEmotionsFeedback">
        <rdfs:subClassOf rdf:resource="&EmotionOntology;EmotionalFeedbackTactic"/>
        <rdfs:comment>控制负向情感反馈策略包括避免和防止负向情感的产生、控制负向情感的发展、减轻负向情感和将负向情感转化为正向情感，</rdfs:comment>
    </owl:Class>
```

```
    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Criticism
-->

    <owl:Class rdf:about="&EmotionOntology;Criticism">
        <rdfs:subClassOf
rdf:resource="&EmotionOntology;NegativeEmotionsFeedback"/>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Emotiona
lFeedbackTactic -->

    <owl:Class rdf:about="&EmotionOntology;EmotionalFeedbackTactic"/>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Emotiona
lState -->

    <owl:Class rdf:about="&EmotionOntology;EmotionalState">
        <rdfs:subClassOf rdf:resource="&owl;Thing"/>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Encoding
-->

    <owl:Class rdf:about="&EmotionOntology;Encoding">
        <rdfs:subClassOf rdf:resource="&EmotionOntology;CognitiveState"/>
        <rdfs:comment>providing learning guidance</rdfs:comment>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Encourag
ement -->
```

```
    <owl:Class rdf:about="&EmotionOntology;Encouragement">
        <rdfs:subClassOf
rdf:resource="&EmotionOntology;ControlOfNegativeEmotionsFeedback"/>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#EnterNex
tStep -->

    <owl:Class rdf:about="&EmotionOntology;EnterNextStep">
        <rdfs:subClassOf
rdf:resource="&EmotionOntology;CognitiveFeedbackTactic"/>
        <rdfs:comment>表示进入下一个片段观看</rdfs:comment>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Entertain
ment -->

    <owl:Class rdf:about="&EmotionOntology;Entertainment">
        <rdfs:subClassOf
rdf:resource="&EmotionOntology;PositiveEmotionsFeedback"/>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#ExplainA
nswer -->

    <owl:Class rdf:about="&EmotionOntology;ExplainAnswer">
        <rdfs:subClassOf
rdf:resource="&EmotionOntology;CognitiveFeedbackTactic"/>
        <rdfs:comment>表示问答过程中解释答案</rdfs:comment>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Flow -->
```

```
    <owl:Class rdf:about="&EmotionOntology;Flow">
        <rdfs:subClassOf rdf:resource="&EmotionOntology;PositiveEmotion"/>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Frustratio
n -->

    <owl:Class rdf:about="&EmotionOntology;Frustration">
        <rdfs:subClassOf rdf:resource="&EmotionOntology;NegativeEmotion"/>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Gaining
Attention -->

    <owl:Class rdf:about="&EmotionOntology;GainingAttention">
        <rdfs:subClassOf rdf:resource="&EmotionOntology;InstructionalStep"/>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Generalis
ing -->

    <owl:Class rdf:about="&EmotionOntology;Generalising">
        <rdfs:subClassOf rdf:resource="&EmotionOntology;CognitiveState"/>
        <rdfs:comment>enhancing retention and transfer</rdfs:comment>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#GetAtten
tion -->

    <owl:Class rdf:about="&EmotionOntology;GetAttention">
        <rdfs:subClassOf
```

```
rdf:resource="&EmotionOntology;CognitiveFeedbackTactic"/>
          <rdfs:comment>获取学生注意</rdfs:comment>
     </owl:Class>



     <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#GiveAns
wer -->

     <owl:Class rdf:about="&EmotionOntology;GiveAnswer">
          <rdfs:subClassOf
rdf:resource="&EmotionOntology;CognitiveFeedbackTactic"/>
          <rdfs:comment>问答环节给出答案</rdfs:comment>
     </owl:Class>



     <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#GiveExa
mple -->

     <owl:Class rdf:about="&EmotionOntology;GiveExample">
          <rdfs:subClassOf
rdf:resource="&EmotionOntology;CognitiveFeedbackTactic"/>
          <rdfs:comment>对应知识点的举例</rdfs:comment>
     </owl:Class>



     <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#GiveHint
-->

     <owl:Class rdf:about="&EmotionOntology;GiveHint">
          <rdfs:subClassOf
rdf:resource="&EmotionOntology;CognitiveFeedbackTactic"/>
          <rdfs:comment>问答环节的提示</rdfs:comment>
     </owl:Class>



     <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#GoOn -->
```

```
	<owl:Class rdf:about="&EmotionOntology;GoOn">
		<rdfs:subClassOf
rdf:resource="&EmotionOntology;CognitiveFeedbackTactic"/>
		<rdfs:comment>表示继续本视频片段的观看</rdfs:comment>
	</owl:Class>



	<!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Goodwill
-->

	<owl:Class rdf:about="&EmotionOntology;Goodwill">
		<rdfs:subClassOf
rdf:resource="&EmotionOntology;PositiveEmotionsFeedback"/>
	</owl:Class>



	<!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Happines
s -->

	<owl:Class rdf:about="&EmotionOntology;Happiness">
		<rdfs:subClassOf rdf:resource="&EmotionOntology;PositiveEmotion"/>
	</owl:Class>



	<!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Humor
-->

	<owl:Class rdf:about="&EmotionOntology;Humor">
		<rdfs:subClassOf
rdf:resource="&EmotionOntology;PositiveEmotionsFeedback"/>
	</owl:Class>



	<!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Informin
gObjective -->
```

```
    <owl:Class rdf:about="&EmotionOntology;InformingObjective">
        <rdfs:subClassOf rdf:resource="&EmotionOntology;InstructionalStep"/>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Instructio
nalStep -->

    <owl:Class rdf:about="&EmotionOntology;InstructionalStep"/>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Interest
-->

    <owl:Class rdf:about="&EmotionOntology;Interest">
        <rdfs:subClassOf rdf:resource="&EmotionOntology;PositiveEmotion"/>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#KDPoint
-->

    <owl:Class rdf:about="&EmotionOntology;KDPoint"/>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Learning
Capability -->

    <owl:Class rdf:about="&EmotionOntology;LearningCapability"/>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Negative
CogState -->
```

```
    <owl:Class rdf:about="&EmotionOntology;NegativeCogState">
        <rdfs:subClassOf rdf:resource="&EmotionOntology;CognitiveState"/>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Negative
Emotion -->

    <owl:Class rdf:about="&EmotionOntology;NegativeEmotion">
        <rdfs:subClassOf rdf:resource="&EmotionOntology;EmotionalState"/>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Negative
EmotionsFeedback -->

    <owl:Class rdf:about="&EmotionOntology;NegativeEmotionsFeedback">
        <rdfs:subClassOf
rdf:resource="&EmotionOntology;EmotionalFeedbackTactic"/>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#NoEmoF
eedback -->

    <owl:Class rdf:about="&EmotionOntology;NoEmoFeedback">
        <rdfs:subClassOf
rdf:resource="&EmotionOntology;EmotionalFeedbackTactic"/>
            <owl:disjointUnionOf rdf:parseType="Collection">
                <rdf:Description
rdf:about="&EmotionOntology;ControlOfNegativeEmotionsFeedback"/>
                <rdf:Description
rdf:about="&EmotionOntology;NegativeEmotionsFeedback"/>
                <rdf:Description
rdf:about="&EmotionOntology;PositiveEmotionsFeedback"/>
            </owl:disjointUnionOf>
    </owl:Class>
```

```
    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Pause -->

    <owl:Class rdf:about="&EmotionOntology;Pause">
        <rdfs:subClassOf
rdf:resource="&EmotionOntology;CognitiveFeedbackTactic"/>
        <rdfs:comment>暂停，目的是让学生有思考的时间。</rdfs:comment>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Perceivin
g -->

    <owl:Class rdf:about="&EmotionOntology;Perceiving">
        <rdfs:subClassOf rdf:resource="&EmotionOntology;CognitiveState"/>
        <rdfs:comment>presenting the stimulus</rdfs:comment>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Personali
tyTraits -->

    <owl:Class rdf:about="&EmotionOntology;PersonalityTraits"/>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#PositiveC
ogState -->

    <owl:Class rdf:about="&EmotionOntology;PositiveCogState">
        <rdfs:subClassOf rdf:resource="&EmotionOntology;CognitiveState"/>
    </owl:Class>



    <!--
```

```
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#PositiveE
motion -->

    <owl:Class rdf:about="&EmotionOntology;PositiveEmotion">
        <rdfs:subClassOf rdf:resource="&EmotionOntology;EmotionalState"/>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#PositiveE
motionsFeedback -->

    <owl:Class rdf:about="&EmotionOntology;PositiveEmotionsFeedback">
        <rdfs:subClassOf
rdf:resource="&EmotionOntology;EmotionalFeedbackTactic"/>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#PositiveS
urprise -->

    <owl:Class rdf:about="&EmotionOntology;PositiveSurprise">
        <rdfs:subClassOf
rdf:resource="&EmotionOntology;PositiveEmotionsFeedback"/>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Praise -->

    <owl:Class rdf:about="&EmotionOntology;Praise">
        <rdfs:subClassOf
rdf:resource="&EmotionOntology;PositiveEmotionsFeedback"/>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Presentin
gStimulus -->
```

```
    <owl:Class rdf:about="&EmotionOntology;PresentingStimulus">
        <rdfs:subClassOf rdf:resource="&EmotionOntology;InstructionalStep"/>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Providin
gLearningGuidance -->

    <owl:Class rdf:about="&EmotionOntology;ProvidingLearningGuidance">
        <rdfs:subClassOf rdf:resource="&EmotionOntology;InstructionalStep"/>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Punishm
ent -->

    <owl:Class rdf:about="&EmotionOntology;Punishment">
        <rdfs:subClassOf
rdf:resource="&EmotionOntology;NegativeEmotionsFeedback"/>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Receptin
g -->

    <owl:Class rdf:about="&EmotionOntology;Recepting">
        <rdfs:subClassOf rdf:resource="&EmotionOntology;CognitiveState"/>
        <rdfs:comment>gaining attention</rdfs:comment>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Reinforci
ng -->

    <owl:Class rdf:about="&EmotionOntology;Reinforcing">
```

```
        <rdfs:subClassOf rdf:resource="&EmotionOntology;CognitiveState"/>
        <rdfs:comment>providing feedback</rdfs:comment>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Relief -->

    <owl:Class rdf:about="&EmotionOntology;Relief">
        <rdfs:subClassOf
rdf:resource="&EmotionOntology;ControlOfNegativeEmotionsFeedback"/>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Repeat
-->

    <owl:Class rdf:about="&EmotionOntology;Repeat">
        <rdfs:subClassOf
rdf:resource="&EmotionOntology;CognitiveFeedbackTactic"/>
        <rdfs:comment>重复本片段</rdfs:comment>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Respondi
ng -->

    <owl:Class rdf:about="&EmotionOntology;Responding">
        <rdfs:subClassOf rdf:resource="&EmotionOntology;CognitiveState"/>
        <rdfs:comment>eliciting performance</rdfs:comment>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Retrievin
g -->

    <owl:Class rdf:about="&EmotionOntology;Retrieving">
```

```
        <rdfs:subClassOf rdf:resource="&EmotionOntology;CognitiveState"/>
        <rdfs:comment>stimulating recall of prior learning</rdfs:comment>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#ReviewP
rerequisiteKnowledge -->

    <owl:Class rdf:about="&EmotionOntology;ReviewPrerequisiteKnowledge">
        <rdfs:subClassOf
rdf:resource="&EmotionOntology;CognitiveFeedbackTactic"/>
        <rdfs:comment>复习前序知识点</rdfs:comment>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Reward
-->

    <owl:Class rdf:about="&EmotionOntology;Reward">
        <rdfs:subClassOf
rdf:resource="&EmotionOntology;PositiveEmotionsFeedback"/>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#SelectLe
arningUnit -->

    <owl:Class rdf:about="&EmotionOntology;SelectLearningUnit">
        <rdfs:subClassOf
rdf:resource="&EmotionOntology;CognitiveFeedbackTactic"/>
        <rdfs:comment>选择学习单元</rdfs:comment>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Standard
Answer -->
```

```
    <owl:Class rdf:about="&EmotionOntology;StandardAnswer"/>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Stimulati
ngRecall -->

    <owl:Class rdf:about="&EmotionOntology;StimulatingRecall">
        <rdfs:subClassOf rdf:resource="&EmotionOntology;InstructionalStep"/>
    </owl:Class>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#StuAnsw
er -->

    <owl:Class rdf:about="&EmotionOntology;StuAnswer"/>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Student
-->

    <owl:Class rdf:about="&EmotionOntology;Student"/>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#Sympath
y -->

    <owl:Class rdf:about="&EmotionOntology;Sympathy">
        <rdfs:subClassOf
rdf:resource="&EmotionOntology;ControlOfNegativeEmotionsFeedback"/>
    </owl:Class>



    <!-- http://www.w3.org/2002/07/owl#Thing -->
```

```
    <owl:Class rdf:about="&owl;Thing"/>



    <!--
    ///////////////////////////////////////////////////////////////////////////////////////
    //
    // Individuals
    //
    ///////////////////////////////////////////////////////////////////////////////////////
     -->




    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#acceptan
ce -->

    <owl:Thing rdf:about="&EmotionOntology;acceptance">
        <rdf:type rdf:resource="&EmotionOntology;Acceptance"/>
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
        <hasText rdf:datatype="&xsd;string">Good！</hasText>
        <hasText rdf:datatype="&xsd;string">好的。</hasText>
    </owl:Thing>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#anticipati
ng -->

    <owl:Thing rdf:about="&EmotionOntology;anticipating">
        <rdf:type rdf:resource="&EmotionOntology;Anticipating"/>
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
        <isAssociatedwith rdf:resource="&EmotionOntology;boredom"/>
        <isAssociatedwith rdf:resource="&EmotionOntology;confusion"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;criticism"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;encouragement"/>
        <isAssociatedwith rdf:resource="&EmotionOntology;flow"/>
        <isAssociatedwith rdf:resource="&EmotionOntology;frustration"/>
        <hasEmotionalFeedbackTactic
```

```
rdf:resource="&EmotionOntology;goodwill"/>
        <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;goon"/>
        <isAssociatedwith rdf:resource="&EmotionOntology;happiness"/>
        <isAssociatedwith rdf:resource="&EmotionOntology;interest"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;noemofeedback"/>
        <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;relief"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;selectlearningunit"/>
    </owl:Thing>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#boredom
-->

    <owl:Thing rdf:about="&EmotionOntology;boredom">
        <rdf:type rdf:resource="&EmotionOntology;Boredom"/>
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;acceptance"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;criticism"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;encouragement"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;enternextstep"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;explainanswer"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;getattention"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;giveanswer"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;giveexample"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;givehint"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;positivesurprise"/>
        <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;relief"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;reviewprerequisiteknowledgepoint"/>
        <hasCognitiveFeedbackTactic
```

```
rdf:resource="&EmotionOntology;selectlearningunit"/>
                <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;sympathy"/>
        </owl:Thing>



        <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#confusio
n -->

        <owl:Thing rdf:about="&EmotionOntology;confusion">
                <rdf:type rdf:resource="&EmotionOntology;Confusion"/>
                <rdf:type rdf:resource="&owl;NamedIndividual"/>
                <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;encouragement"/>
                <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;explainanswer"/>
                <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;giveanswer"/>
                <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;giveexample"/>
                <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;givehint"/>
                <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;goodwill"/>
                <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;pause"/>
                <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;relief"/>
                <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;repeat"/>
                <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;reviewprerequisiteknowledgepoint"/>
                <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;selectlearningunit"/>
                <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;sympathy"/>
        </owl:Thing>



        <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#congratul
ation -->

        <owl:Thing rdf:about="&EmotionOntology;congratulation">
```

```
            <rdf:type rdf:resource="&EmotionOntology;Congratulation"/>
            <rdf:type rdf:resource="&owl;NamedIndividual"/>
        </owl:Thing>



        <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#criticism
-->

        <owl:Thing rdf:about="&EmotionOntology;criticism">
            <rdf:type rdf:resource="&EmotionOntology;Criticism"/>
            <rdf:type rdf:resource="&owl;NamedIndividual"/>
        </owl:Thing>



        <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#encoding
-->

        <owl:Thing rdf:about="&EmotionOntology;encoding">
            <rdf:type rdf:resource="&EmotionOntology;Encoding"/>
            <rdf:type rdf:resource="&owl;NamedIndividual"/>
            <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;acceptance"/>
            <isAssociatedwith rdf:resource="&EmotionOntology;boredom"/>
            <isAssociatedwith rdf:resource="&EmotionOntology;confusion"/>
            <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;encouragement"/>
            <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;enternextstep"/>
            <isAssociatedwith rdf:resource="&EmotionOntology;flow"/>
            <isAssociatedwith rdf:resource="&EmotionOntology;frustration"/>
            <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;giveexample"/>
            <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;goon"/>
            <isAssociatedwith rdf:resource="&EmotionOntology;happiness"/>
            <isAssociatedwith rdf:resource="&EmotionOntology;interest"/>
            <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;pause"/>
            <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;positivesurprise"/>
            <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;praise"/>
            <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;relief"/>
```

```
            <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;repeat"/>
            <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;reviewprerequisiteknowledgepoint"/>
            <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;sympathy"/>
        </owl:Thing>



        <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#encourag
ement -->

        <owl:Thing rdf:about="&EmotionOntology;encouragement">
            <rdf:type rdf:resource="&EmotionOntology;Encouragement"/>
            <rdf:type rdf:resource="&owl;NamedIndividual"/>
        </owl:Thing>



        <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#enternext
step -->

        <owl:Thing rdf:about="&EmotionOntology;enternextstep">
            <rdf:type rdf:resource="&EmotionOntology;EnterNextStep"/>
            <rdf:type rdf:resource="&owl;NamedIndividual"/>
        </owl:Thing>



        <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#entertain
ment -->

        <owl:Thing rdf:about="&EmotionOntology;entertainment">
            <rdf:type rdf:resource="&EmotionOntology;Entertainment"/>
            <rdf:type rdf:resource="&owl;NamedIndividual"/>
        </owl:Thing>



        <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#explainan
```

```
swer -->

    <owl:Thing rdf:about="&EmotionOntology;explainanswer">
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
    </owl:Thing>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#flow -->

    <owl:Thing rdf:about="&EmotionOntology;flow">
        <rdf:type rdf:resource="&EmotionOntology;Flow"/>
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;congratulation"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;encouragement"/>
        <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;goon"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;noemofeedback"/>
        <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;praise"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;reward"/>
    </owl:Thing>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#frustratio
n -->

    <owl:Thing rdf:about="&EmotionOntology;frustration">
        <rdf:type rdf:resource="&EmotionOntology;Frustration"/>
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;encouragement"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;explainanswer"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;giveanswer"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;giveexample"/>
        <hasCognitiveFeedbackTactic
```

```
rdf:resource="&EmotionOntology;givehint"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;goodwill"/>
        <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;relief"/>
        <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;repeat"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;reviewprerequisiteknowledgepoint"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;selectlearningunit"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;sympathy"/>
    </owl:Thing>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#generalisi
ng -->

    <owl:Thing rdf:about="&EmotionOntology;generalising">
        <rdf:type rdf:resource="&EmotionOntology;Generalising"/>
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;acceptance"/>
        <isAssociatedwith rdf:resource="&EmotionOntology;boredom"/>
        <isAssociatedwith rdf:resource="&EmotionOntology;confusion"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;encouragement"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;enternextstep"/>
        <isAssociatedwith rdf:resource="&EmotionOntology;flow"/>
        <isAssociatedwith rdf:resource="&EmotionOntology;frustration"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;giveexample"/>
        <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;goon"/>
        <isAssociatedwith rdf:resource="&EmotionOntology;happiness"/>
        <isAssociatedwith rdf:resource="&EmotionOntology;interest"/>
        <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;pause"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;positivesurprise"/>
        <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;praise"/>
        <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;relief"/>
        <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;repeat"/>
        <hasCognitiveFeedbackTactic
```

```
rdf:resource="&EmotionOntology;reviewprerequisiteknowledgepoint"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;sympathy"/>
    </owl:Thing>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#getattenti
on -->

    <owl:Thing rdf:about="&EmotionOntology;getattention">
        <rdf:type rdf:resource="&EmotionOntology;GetAttention"/>
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
    </owl:Thing>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#giveansw
er -->

    <owl:Thing rdf:about="&EmotionOntology;giveanswer">
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
    </owl:Thing>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#giveexam
ple -->

    <owl:Thing rdf:about="&EmotionOntology;giveexample">
        <rdf:type rdf:resource="&EmotionOntology;GiveExample"/>
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
    </owl:Thing>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#givehint
-->

    <owl:Thing rdf:about="&EmotionOntology;givehint">
```

```
        <rdf:type rdf:resource="&EmotionOntology;GiveHint"/>
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
    </owl:Thing>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#goodwill
-->

    <owl:Thing rdf:about="&EmotionOntology;goodwill">
        <rdf:type rdf:resource="&EmotionOntology;Goodwill"/>
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
    </owl:Thing>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#goon -->

    <owl:Thing rdf:about="&EmotionOntology;goon">
        <rdf:type rdf:resource="&EmotionOntology;GoOn"/>
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
    </owl:Thing>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#happines
s -->

    <owl:Thing rdf:about="&EmotionOntology;happiness">
        <rdf:type rdf:resource="&EmotionOntology;Happiness"/>
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;congratulation"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;encouragement"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;goodwill"/>
        <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;goon"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;positivesurprise"/>
        <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;praise"/>
```

```
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;reward"/>
    </owl:Thing>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#humor
-->

    <owl:Thing rdf:about="&EmotionOntology;humor">
        <rdf:type rdf:resource="&EmotionOntology;Humor"/>
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
    </owl:Thing>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#interest
-->

    <owl:Thing rdf:about="&EmotionOntology;interest">
        <rdf:type rdf:resource="&EmotionOntology;Interest"/>
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;encouragement"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;explainanswer"/>
        <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;goon"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;noemofeedback"/>
        <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;praise"/>
    </owl:Thing>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#memorisi
ng -->

    <owl:Thing rdf:about="&EmotionOntology;memorising">
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;encouragement"/>
```

```
            <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;enternextstep"/>
            <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;giveexample"/>
            &lt;hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;goon"/&gt;
            &lt;hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;praise"/&gt;
            &lt;hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;relief"/&gt;
            &lt;hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;repeat"/&gt;
            <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;reviewprerequisiteknowledgepoint"/>
        &lt;/owl:Thing&gt;



        <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#negativec
ogstate -->

        &lt;owl:Thing rdf:about="&EmotionOntology;negativecogstate"&gt;
            &lt;rdf:type rdf:resource="&EmotionOntology;NegativeCogState"/&gt;
            &lt;rdf:type rdf:resource="&owl;NamedIndividual"/&gt;
            <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;criticism"/>
            <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;encouragement"/>
            <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;explainanswer"/>
            <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;getattention"/>
            <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;giveexample"/>
            <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;givehint"/>
            <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;goodwill"/>
            &lt;hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;relief"/&gt;
            <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;reviewprerequisiteknowledgepoint"/>
            <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;selectlearningunit"/>
            <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;sympathy"/>
        &lt;/owl:Thing&gt;
```

```
    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#noemofe
edback -->

    <owl:NamedIndividual rdf:about="&EmotionOntology;noemofeedback">
        <rdf:type rdf:resource="&EmotionOntology;NoEmoFeedback"/>
    </owl:NamedIndividual>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#pause -->

    <owl:Thing rdf:about="&EmotionOntology;pause">
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
    </owl:Thing>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#perceivin
g -->

    <owl:Thing rdf:about="&EmotionOntology;perceiving">
        <rdf:type rdf:resource="&EmotionOntology;Perceiving"/>
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;acceptance"/>
        <isAssociatedwith rdf:resource="&EmotionOntology;boredom"/>
        <isAssociatedwith rdf:resource="&EmotionOntology;confusion"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;encouragement"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;enternextstep"/>
        <isAssociatedwith rdf:resource="&EmotionOntology;flow"/>
        <isAssociatedwith rdf:resource="&EmotionOntology;frustration"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;giveexample"/>
        <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;goon"/>
        <isAssociatedwith rdf:resource="&EmotionOntology;happiness"/>
        <isAssociatedwith rdf:resource="&EmotionOntology;interest"/>
        <hasEmotionalFeedbackTactic
```

```
rdf:resource="&EmotionOntology;noemofeedback"/>
        <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;pause"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;positivesurprise"/>
        <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;praise"/>
        <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;relief"/>
        <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;repeat"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;reviewprerequisiteknowledgepoint"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;sympathy"/>
    </owl:Thing>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#positivec
ogstate -->

    <owl:Thing rdf:about="&EmotionOntology;positivecogstate">
        <rdf:type rdf:resource="&EmotionOntology;PositiveCogState"/>
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;acceptance"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;enternextstep"/>
        <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;goon"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;positivesurprise"/>
        <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;praise"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;selectlearningunit"/>
    </owl:Thing>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#positives
urprise -->

    <owl:Thing rdf:about="&EmotionOntology;positivesurprise">
        <rdf:type rdf:resource="&EmotionOntology;PositiveSurprise"/>
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
    </owl:Thing>
```

```
    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#praise -->

    <owl:Thing rdf:about="&EmotionOntology;praise">
        <rdf:type rdf:resource="&EmotionOntology;Praise"/>
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
    </owl:Thing>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#punishme
nt -->

    <owl:Thing rdf:about="&EmotionOntology;punishment">
        <rdf:type rdf:resource="&EmotionOntology;Punishment"/>
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
    </owl:Thing>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#recalling
-->

    <owl:Thing rdf:about="&EmotionOntology;recalling">
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
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        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;encouragement"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;enternextstep"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;giveexample"/>
        <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;goon"/>
        <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;praise"/>
        <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;relief"/>
        <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;repeat"/>
    </owl:Thing>
```

```
    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#recepting
-->

    <owl:Thing rdf:about="&EmotionOntology;recepting">
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        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;criticism"/>
        <isAssociatedwith rdf:resource="&EmotionOntology;flow"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;getattention"/>
        <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;goon"/>
        <isAssociatedwith rdf:resource="&EmotionOntology;happiness"/>
        <isAssociatedwith rdf:resource="&EmotionOntology;interest"/>
        <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;praise"/>
    </owl:Thing>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#reinforci
ng -->

    <owl:Thing rdf:about="&EmotionOntology;reinforcing">
        <rdf:type rdf:resource="&EmotionOntology;Reinforcing"/>
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
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rdf:resource="&EmotionOntology;acceptance"/>
        <isAssociatedwith rdf:resource="&EmotionOntology;boredom"/>
        <isAssociatedwith rdf:resource="&EmotionOntology;confusion"/>
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rdf:resource="&EmotionOntology;congratulation"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;encouragement"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;enternextstep"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;explainanswer"/>
        <isAssociatedwith rdf:resource="&EmotionOntology;frustration"/>
        <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;goon"/>
```

```
            <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;pause"/>
            <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;positivesurprise"/>
            <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;praise"/>
            <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;relief"/>
            <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;reward"/>
            <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;sympathy"/>
      </owl:Thing>



      <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#relief -->

      <owl:Thing rdf:about="&EmotionOntology;relief">
            <rdf:type rdf:resource="&EmotionOntology;Relief"/>
            <rdf:type rdf:resource="&owl;NamedIndividual"/>
      </owl:Thing>



      <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#repeat -->

      <owl:Thing rdf:about="&EmotionOntology;repeat">
            <rdf:type rdf:resource="&EmotionOntology;Repeat"/>
            <rdf:type rdf:resource="&owl;NamedIndividual"/>
      </owl:Thing>



      <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#respondi
ng -->

      <owl:Thing rdf:about="&EmotionOntology;responding">
            <rdf:type rdf:resource="&EmotionOntology;Responding"/>
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rdf:resource="&EmotionOntology;acceptance"/>
            <isAssociatedwith rdf:resource="&EmotionOntology;confusion"/>
            <hasEmotionalFeedbackTactic
```

```
rdf:resource="&EmotionOntology;encouragement"/>
            <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;enternextstep"/>
            <isAssociatedwith rdf:resource="&EmotionOntology;frustration"/>
            <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;giveanswer"/>
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rdf:resource="&EmotionOntology;givehint"/>
            <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;goodwill"/>
            <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;goon"/>
            <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;pause"/>
            <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;positivesurprise"/>
            <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;relief"/>
            <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;reviewprerequisiteknowledgepoint"/>
            <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;sympathy"/>
      </owl:Thing>



      <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#retrieving
-->

      <owl:Thing rdf:about="&EmotionOntology;retrieving">
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            <rdf:type rdf:resource="&owl;NamedIndividual"/>
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rdf:resource="&EmotionOntology;acceptance"/>
            <isAssociatedwith rdf:resource="&EmotionOntology;boredom"/>
            <isAssociatedwith rdf:resource="&EmotionOntology;confusion"/>
            <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;encouragement"/>
            <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;enternextstep"/>
            <isAssociatedwith rdf:resource="&EmotionOntology;flow"/>
            <isAssociatedwith rdf:resource="&EmotionOntology;frustration"/>
            <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;goon"/>
            <isAssociatedwith rdf:resource="&EmotionOntology;happiness"/>
            <isAssociatedwith rdf:resource="&EmotionOntology;interest"/>
            <hasEmotionalFeedbackTactic
```

```
rdf:resource="&EmotionOntology;noemofeedback"/>
            <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;pause"/>
            <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;praise"/>
            <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;relief"/>
            <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;repeat"/>
            <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;reviewprerequisiteknowledgepoint"/>
            <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;sympathy"/>
      </owl:Thing>



      <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#reviewpr
erequisiteknowledgepoint -->

      <owl:Thing
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rdf:resource="&EmotionOntology;ReviewPrerequisiteKnowledge"/>
            <rdf:type rdf:resource="&owl;NamedIndividual"/>
      </owl:Thing>



      <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#reward
-->

      <owl:Thing rdf:about="&EmotionOntology;reward">
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            <rdf:type rdf:resource="&owl;NamedIndividual"/>
      </owl:Thing>



      <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#selectlear
ningunit -->

      <owl:Thing rdf:about="&EmotionOntology;selectlearningunit">
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            <rdf:type rdf:resource="&owl;NamedIndividual"/>
```

```
    </owl:Thing>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#solvingpr
oblem -->

    <owl:Thing rdf:about="&EmotionOntology;solvingproblem">
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rdf:resource="&EmotionOntology;acceptance"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;congratulation"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;encouragement"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;giveexample"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;givehint"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;goodwill"/>
        <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;goon"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;positivesurprise"/>
        <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;praise"/>
        <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;relief"/>
        <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;repeat"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;reviewprerequisiteknowledgepoint"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;reward"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;sympathy"/>
    </owl:Thing>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#sympathy
-->

    <owl:Thing rdf:about="&EmotionOntology;sympathy">
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```

```
        <rdf:type rdf:resource="&owl;NamedIndividual"/>
    </owl:Thing>



    <!--
http://www.owl-ontologies.com/marine.owl/2011/11/EmotionOntology.owl#understan
ding -->

    <owl:Thing rdf:about="&EmotionOntology;understanding">
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rdf:resource="&EmotionOntology;encouragement"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;enternextstep"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;giveexample"/>
        <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;goon"/>
        <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;praise"/>
        <hasEmotionalFeedbackTactic rdf:resource="&EmotionOntology;relief"/>
        <hasCognitiveFeedbackTactic rdf:resource="&EmotionOntology;repeat"/>
        <hasCognitiveFeedbackTactic
rdf:resource="&EmotionOntology;reviewprerequisiteknowledgepoint"/>
        <hasEmotionalFeedbackTactic
rdf:resource="&EmotionOntology;sympathy"/>
    </owl:Thing>



    <!--
    ///////////////////////////////////////////////////////////////////////////////////////
    //
    // General axioms
    //
    ///////////////////////////////////////////////////////////////////////////////////////
     -->

    <rdf:Description>
        <rdf:type rdf:resource="&owl;AllDisjointClasses"/>
        <owl:members rdf:parseType="Collection">
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            <rdf:Description rdf:about="&EmotionOntology;Encoding"/>
```

```
                <rdf:Description rdf:about="&EmotionOntology;Generalising"/>
                <rdf:Description rdf:about="&EmotionOntology;NegativeCogState"/>
                <rdf:Description rdf:about="&EmotionOntology;Perceiving"/>
                <rdf:Description rdf:about="&EmotionOntology;PositiveCogState"/>
                <rdf:Description rdf:about="&EmotionOntology;Recepting"/>
                <rdf:Description rdf:about="&EmotionOntology;Reinforcing"/>
                <rdf:Description rdf:about="&EmotionOntology;Responding"/>
                <rdf:Description rdf:about="&EmotionOntology;Retrieving"/>
            </owl:members>
        </rdf:Description>
        <rdf:Description>
            <rdf:type rdf:resource="&owl;AllDisjointClasses"/>
            <owl:members rdf:parseType="Collection">
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                <rdf:Description rdf:about="&EmotionOntology;GetAttention"/>
                <rdf:Description rdf:about="&EmotionOntology;GiveExample"/>
                <rdf:Description rdf:about="&EmotionOntology;GiveHint"/>
                <rdf:Description rdf:about="&EmotionOntology;GoOn"/>
                <rdf:Description rdf:about="&EmotionOntology;Repeat"/>
                <rdf:Description
rdf:about="&EmotionOntology;ReviewPrerequisiteKnowledge"/>
                <rdf:Description
rdf:about="&EmotionOntology;SelectLearningUnit"/>
            </owl:members>
        </rdf:Description>
        <rdf:Description>
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            <owl:members rdf:parseType="Collection">
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                <rdf:Description
rdf:about="&EmotionOntology;NegativeEmotionsFeedback"/>
                <rdf:Description
rdf:about="&EmotionOntology;PositiveEmotionsFeedback"/>
            </owl:members>
        </rdf:Description>
</rdf:RDF>



<!-- Generated by the OWL API (version 3.4.2) http://owlapi.sourceforge.net -->
```

Appendix B Cases in the evaluation

Cases used in stage 2 of the evaluation:

Case ID: 1

Student information:

Emotional state: Interest Cognitive state: Anticipating

PrerequisiteKP mastered?: 0.85 Student capability: 0.85

KP difficulty level: 1

Feedback information:

Cognitive Feedback tactic 1: goon Emotional Feedback tactic 1: noemofeedback

Feedback1: 继续播放视频

Translation of feedback1: No emotional feedback, go on playing the video.

Cognitive Feedback tactic 2: goon Emotional Feedback tactic 2: encouragement

Feedback2: “加油！”+继续播放视频

Translation of feedback2: Come on! Go on playing the video.

Cognitive Feedback tactic 3: pause Emotional Feedback tactic 3: relief

Feedback3: 不紧张，我们停下来想想看。

Translation of feedback3: Take it easy, let's pause and think about it.

Video information:

Begin time: 00:00:04 End time: 00:00:12 Duration: 8 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 2

Student information:

Emotional state: Boredom Cognitive state: Retrieving

PrerequisiteKP mastered?: 0.85 Student capability: 0.85

KP difficulty level: 1

Feedback information:

Cognitive Feedback tactic 1: enternextstep Emotional Feedback tactic 1: acceptance

Feedback1: “好的，让我们跳过这点。”从下段开始（数组名的含义，第 27 秒）继续播放。

Translation of feedback1: Ok, let's move to next section.(Play the video form 27")

Cognitive Feedback tactic 2: enternextstep Emotional Feedback tactic 2: acceptance

Feedback2: 同反馈 1

Translation of feedback2: The same with Feedback 1.

Cognitive Feedback tactic 3: pause Emotional Feedback tactic 3: relief

Feedback3: 不要急，让我们重复再看一次。

Translation of feedback3: No rush, pause and think about it again.

Video information:

Begin time: 00:00:15 End time: 00:00:21 Duration: 6 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 3

Student information:

Emotional state: Flow Cognitive state: Perceiving

PrerequisiteKP mastered?: 0.85 Student capability: 0.85

KP difficulty level: 2

Feedback information:

Cognitive Feedback tactic 1: goon Emotional Feedback tactic 1: noemofeedback

Feedback1: 继续播放视频

Translation of feedback1: No emotional feedback, go on playing the video.

Cognitive Feedback tactic 2: goon Emotional Feedback tactic 2: praise

Feedback2: 你真棒！继续播放视频。

Translation of feedback2: You are great! Go on playing the video.

Cognitive Feedback tactic 3: pause Emotional Feedback tactic 3: relief

Feedback3: 放松点，再琢磨一下。

Translation of feedback3: Take it easy, pause and think about it again.

Video information:

Begin time: 00:02:24 End time: 00:02:35 Duration: 11 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 4

Student information:

Emotional state: Confusion   Cognitive state: Encoding

PrerequisiteKP mastered?: 0.50 Student capability: 0.85

KP difficulty level: 3

Feedback information:

Cognitive Feedback tactic 1: giveexample Emotional Feedback tactic 1: relief

Feedback1: “别着急，假设 a 数组是 float 的，则 a[i]的地址为 a+i*4。”

Translation of feedback1: No worry. For example, if the type of array a is "float", the address of element a[i] is a+i*4.

Cognitive Feedback tactic 2: pause Emotional Feedback tactic 2: relief

Feedback2: 别着急，我们停下来想想看。

Translation of feedback2: No rush, let's pause and think about it again.

Cognitive Feedback tactic 3: goon Emotional Feedback tactic 3: praise

Feedback3: 你真棒！继续播放视频。

Translation of feedback3: You are great! Go on playing the video.

Video information:

Begin time: 00:03:42 End time: 00:04:00 Duration: 18 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 5

Student information:

Emotional state: Confusion Cognitive state: Perceiving

PrerequisiteKP mastered?: 0.15 Student capability: 0.85

KP difficulty level: 4

Feedback information:

Cognitive Feedback tactic 1: reviewprerequisiteKP Emotional Feedback tactic 1: relief

Feedback1: 放松点，让我们再来看看指针相关的运算符 * 和 [] 的用法。(播放上一讲中讲述指针相关的运算符 * 和 [] 的用法的片段)

Translation of feedback1: Take it easy. Let's review the usage of the pointer operator * and [] in last lecture.(Play from 14'25" to 22'41" CProgrammingZengyi25.flv)

Cognitive Feedback tactic 2: pause Emotional Feedback tactic 2: relief

Feedback2: 放松点，我们停下来仔细想想。

Translation of feedback2: Take it easy, let's pause and think about it carefully again.

Cognitive Feedback tactic 3: goon Emotional Feedback tactic 3: encouragement

Feedback3: “加油！”+继续播放视频

Translation of feedback3: Come on! Go on playing the video.

Video information:

Begin time: 00:05:03 End time: 00:05:50 Duration: 47 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 6

Student information:

Emotional state: Confusion Cognitive state: Perceiving

PrerequisiteKP mastered?: 0.15 Student capability: 0.85

KP difficulty level: 4

Feedback information:

Cognitive Feedback tactic 1: reviewprerequisiteKP Emotional Feedback tactic 1: relief

Feedback1: 别急，a 表示数组的首地址，是常量，值是不能被更新的，但是变量的值可以被更新。

Translation of feedback1: No worry, let's review the meaning of the name of the array. Array's name "a" means the start address of the array. It is a constant and the value of a constant cannot be changed.

Cognitive Feedback tactic 2: pause Emotional Feedback tactic 2: relief

Feedback2: 别急，再仔细想想。

Translation of feedback2: No rush, think about it carefully again.

Cognitive Feedback tactic 3: goon Emotional Feedback tactic 3: praise

Feedback3: 你真棒！继续播放视频。

Translation of feedback3: You are great! Go on playing the video.

Video information:

Begin time: 00:06:29 End time: 00:07:20 Duration: 51 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 7

Student information:

Emotional state: Confusion Cognitive state: Retrieving

PrerequisiteKP mastered?: 0.85 Student capability: 0.50

KP difficulty level: 2

Feedback information:

Cognitive Feedback tactic 1: repeat Emotional Feedback tactic 1: encouragement

Feedback1: 再试着想想，重复再看一次这段。

Translation of feedback1: Try to think it again. Let's repeat this part.

Cognitive Feedback tactic 2: pause Emotional Feedback tactic 2: encouragement

Feedback2: 再试着想想，再仔细想一想。

Translation of feedback2: Try it again and pause.

Cognitive Feedback tactic 3: goon Emotional Feedback tactic 3: encouragement

Feedback3: “加油！”+继续播放视频

Translation of feedback3: Come on! Go on playing the video.

Video information:

Begin time: 00:07:25 End time: 00:07:57 Duration: 32 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 8

Student information:

Emotional state: Confusion Cognitive state: Encoding

PrerequisiteKP mastered?: 0.85 Student capability: 0.50

KP difficulty level: 4

Feedback information:

Cognitive Feedback tactic 1: giveexample Emotional Feedback tactic 1: encouragement

Feedback1: 再想想看。举个例子，当 i=1 的时候，把 a[1]的地址赋给指针变量 p，依此类推。

Translation of feedback1: Try to think it again. For example, when i=1, it is assigning the address of a[1] to pointer p, and so on.

Cognitive Feedback tactic 2: pause Emotional Feedback tactic 2: relief

Feedback2: 不紧张，我们停下来想想看。

Translation of feedback2: Take it easy, let's pause and think about it carefully again.

Cognitive Feedback tactic 3: goon Emotional Feedback tactic 3: praise

Feedback3: 你真棒！继续播放视频。

Translation of feedback3: You are great! Go on playing the video.

Video information:

Begin time: 00:09:09 End time: 00:09:28 Duration: 20 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 9

Student information:

Emotional state: Confusion Cognitive state: Encoding

PrerequisiteKP mastered?: 0.50 Student capability: 0.50

KP difficulty level: 4

Feedback information:

Cognitive Feedback tactic 1: giveexample Emotional Feedback tactic 1: relief

Feedback1: 放松，比如当 i=0 时，p 指向 a[0],*p，也就是 a[0]的值被赋为 1。

Translation of feedback1: Take it easy. For example, when i=0, p points to a[0], the value of *p or a[0] is assigned by 0.

Cognitive Feedback tactic 2: pause Emotional Feedback tactic 2: relief

Feedback2: 放松点，再思考一下。

Translation of feedback2: Take it easy, pause and think about it again.

Cognitive Feedback tactic 3: goon Emotional Feedback tactic 3: encouragement

Feedback3: “加油！”+继续播放视频

Translation of feedback3: Come on! Go on playing the video.

Video information:

Begin time: 00:12:00 End time: 00:12:51 Duration: 50 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 10

Student information:

Emotional state: Boredom Cognitive state: Retrieving

PrerequisiteKP mastered?: 0.85 Student capability: 0.85

KP difficulty level: 1

Feedback information:

Cognitive Feedback tactic 1: enternextstep Emotional Feedback tactic 1: acceptance

Feedback1: 好的，你已经懂了，让我们跳过这点。（从 14 分 7 秒开始播放）

Translation of feedback1: OK, you have understood this. Let's move to next section.(Play the video form 14'7")

Cognitive Feedback tactic 2: enternextstep Emotional Feedback tactic 2: acceptance

Feedback2: 同反馈 1

Translation of feedback2: The same with Feedback 1.

Cognitive Feedback tactic 3: pause Emotional Feedback tactic 3: relief

Feedback3: 别紧张，我们停下来仔细想想。

Translation of feedback3: Take it easy, let's pause and think about it.

Video information:

Begin time: 00:13:30 End time: 00:13:53 Duration: 23 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 11

Student information:

Emotional state: Confusion Cognitive state: Perceiving

PrerequisiteKP mastered?: 0.15 Student capability: 0.50

KP difficulty level: 4

Feedback information:

Cognitive Feedback tactic 1: reviewprerequisiteKP Emotional Feedback tactic 1: relief

Feedback1: 别急，让我们复习一下如何通过指针访问数组元素。（4 分 25 秒至 6 分 20 秒）

Translation of feedback1: No worry, let's review how to access the array elements using pointer.(Play from 4'25" to 6'20")

Cognitive Feedback tactic 2: pause Emotional Feedback tactic 2: relief

Feedback2: 别急，再仔细想想看。

Translation of feedback2: No rush, pause and think about it carefully again.

Cognitive Feedback tactic 3: repeat Emotional Feedback tactic 3: relief

Feedback3: 不要急，让我们重复再看一次。

Translation of feedback3: No rush, let's repeat this part again.

Video information:

Begin time: 00:16:04 End time: 00:16:42 Duration: 38 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 12

Student information:

Emotional state: Confusion Cognitive state: Encoding

PrerequisiteKP mastered?: 0.15 Student capability: 0.50

KP difficulty level: 3

Feedback information:

Cognitive Feedback tactic 1: reviewprerequisiteKP Emotional Feedback tactic 1: relief

Feedback1: 别紧张，我们之前讲过 a+i 就是表示数组元素 a[i]的地址，和&a[i]是一样的。

Translation of feedback1: Take it easy,let's review this: a+i is the address of the array element a[i], the same meaning as &a[i].

Cognitive Feedback tactic 2: pause Emotional Feedback tactic 2: relief

Feedback2: 别紧张，我们停下来仔细想想。

Translation of feedback2: Take it easy, let's pause and think about it carefully again.

Cognitive Feedback tactic 3: goon Emotional Feedback tactic 3: praise

Feedback3: 你真棒！继续播放视频。

Translation of feedback3: You are great! Go on playing the video.

Video information:

Begin time: 00:17:49 End time: 00:17:58 Duration: 9 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 13

Student information:

Emotional state: Confusion Cognitive state: Encoding

PrerequisiteKP mastered?: 0.85 Student capability: 0.15

KP difficulty level: 3

Feedback information:

Cognitive Feedback tactic 1: giveexample Emotional Feedback tactic 1: encouragement

Feedback1: 这点你可以理解的，当 p 指向 a[5]元素的时候，是可以进行+或者-的运算的，而数组指针 a 只能指向数组的起始地址，因此只能+不能-。

Translation of feedback1: Trust yourself, you could understand this. For example, when pointer p points to a[5], the pointer can take the operation of "+" or "-". But array pointer "a" only can point to the start address of the array, and cannot take the operation of "+" or "-".

Cognitive Feedback tactic 2: pause Emotional Feedback tactic 2: relief

Feedback2: 放松点，再琢磨一下。

Translation of feedback2: Take it easy, pause and think about it again.

Cognitive Feedback tactic 3: goon Emotional Feedback tactic 3: encouragement

Feedback3: “加油！”+继续播放视频

Translation of feedback3: Come on! Go on playing the video.

Video information:

Begin time: 00:19:55 End time: 00:20:56 Duration: 61 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 14

Student information:

Emotional state:　Confusion　　Cognitive state:　Encoding

PrerequisiteKP mastered?: 0.85　Student capability: 0.15

KP difficulty level: 4

Feedback information:

Cognitive Feedback tactic 1: repeat　Emotional Feedback tactic 1: encouragement

Feedback1: 不要急，让我们重复再看一次。

Translation of feedback1: No rush, Let's repeat this section .

Cognitive Feedback tactic 2: pause　Emotional Feedback tactic 2: relief

Feedback2: 不要急，再思考思考。

Translation of feedback2: Take it easy, pause and think about it again.

Cognitive Feedback tactic 3: goon　Emotional Feedback tactic 3: praise

Feedback3: 你真棒！继续播放视频。

Translation of feedback3: You are great!　Go on playing the video.

Video information:

Begin time: 00:23:55　End time: 00:24:29　Duration: 34 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 15

Student information:

Emotional state: Happiness Cognitive state: Anticipating

PrerequisiteKP mastered?: 0.50 Student capability: 0.15

KP difficulty level: 2

Feedback information:

Cognitive Feedback tactic 1: goon Emotional Feedback tactic 1: encouragement

Feedback1: 加油，让我们继续吧。

Translation of feedback1: Come on. Go on playing the video.

Cognitive Feedback tactic 2: goon Emotional Feedback tactic 2: encouragement

Feedback2: 同反馈 1

Translation of feedback2: The same with Feedback 1.

Cognitive Feedback tactic 3: repeat Emotional Feedback tactic 3: relief

Feedback3: 不要急，让我们重复再看一次。

Translation of feedback3: No rush, let's repeat this part again.

Video information:

Begin time: 00:25:40 End time: 00:26:05 Duration: 25 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 16

Student information:

Emotional state: Confusion Cognitive state: Encoding

PrerequisiteKP mastered?: 0.50 Student capability: 0.15

KP difficulty level: 4

Feedback information:

Cognitive Feedback tactic 1: repeat Emotional Feedback tactic 1: relief

Feedback1: 放松点，让我们重复再看一次。

Translation of feedback1: Take it easy, Let's repeat this section .

Cognitive Feedback tactic 2: pause Emotional Feedback tactic 2: relief

Feedback2: 放松点，我们停下来再想一想。

Translation of feedback2: Take it easy, let's pause and think about it again.

Cognitive Feedback tactic 3: goon Emotional Feedback tactic 3: praise

Feedback3: 你真棒！继续播放视频。

Translation of feedback3: You are great! Go on playing the video.

Video information:

Begin time: 00:27:09 End time: 00:28:35 Duration: 26 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 17

Student information:

Emotional state: Confusion Cognitive state: Encoding

PrerequisiteKP mastered?: 0.15 Student capability: 0.15

KP difficulty level: 5

Feedback information:

Cognitive Feedback tactic 1: reviewprerequisiteKP Emotional Feedback tactic 1: relief

Feedback1: 不急，回忆一下，*q++运算是先执行*运算，再执行++操作。"*q++=*p++;"是 等价于"*q=*p; q++; p++;"的

Translation of feedback1: No rush, let's review this: *q++ is operating * first, then ++. "*q++=*p++;" is equivalent to "*q=*p; q++; p++;".

Cognitive Feedback tactic 2: reviewprerequisiteKP Emotional Feedback tactic 2: relief

Feedback2: 同反馈 1

Translation of feedback2: The same with Feedback 1.

Cognitive Feedback tactic 3: goon Emotional Feedback tactic 3: encouragement

Feedback3: “加油！”+继续播放视频

Translation of feedback3: Come on! Go on playing the video.

Video information:

Begin time: 00:29:01 End time: 00:29:42 Duration: 41 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 18

Student information:

Emotional state:　Frustration　　Cognitive state:　Reinforcing

PrerequisiteKP mastered?: 0.15　Student capability: 0.15

KP difficulty level: 5

Feedback information:

Cognitive Feedback tactic 1: explainanswer　Emotional Feedback tactic 1: sympathy

Feedback1: 我也觉得这点不容易，解释一下是因为上个 for 循环结束的时候 q 已经是指向数组末尾即 a[9]元素之后，如果不重新让 q 指向数组的起始地址就运行*q++，那么就超出数组元素的范围了。

Translation of feedback1: I know this is difficult. Let me explain this. When last "for loop" ends, q points to the end of the array, namely after a[9]. If q is not be assiged with the start address of the arry again, and excecute *q++ next, the address where q points to is out of

Cognitive Feedback tactic 2: explainanswer　Emotional Feedback tactic 2: sympathy

Feedback2: 同反馈 1

Translation of feedback2: The same with Feedback 1.

Cognitive Feedback tactic 3: goon　Emotional Feedback tactic 3: praise

Feedback3: 你真棒！继续播放视频。

Translation of feedback3: You are great!　Go on playing the video.

Video information:

Begin time: 00:30:05　End time: 00:30:54　Duration: 49 seconds

Video file name: CProgrammingZengyi25.flv

Cases used in stage 3 of the evaluation:

Case ID: 1

Student information:

Emotional state: Positive Cognitive state: Anticipating

PrerequisiteKP mastered?: 0.85 Student capability: 0.85

KP difficulty level: 1

Feedback information:

Cognitive Feedback tactic 1: noemofeedback Emotional Feedback tactic 1: goon

Feedback1: 继续播放视频

Translation of feedback1: No emotional feedback, go on playing the video.

Cognitive Feedback tactic 2: noemofeedback Emotional Feedback tactic 2:

Feedback2: 继续播放视频

Translation of feedback2: Go on playing the video.

Cognitive Feedback tactic 3: relief Emotional Feedback tactic 3: pause

Feedback3: 不紧张，我们停下来想想看。

Translation of feedback3: Take it easy, let's pause and think about it.

Video information:

Begin time: 00:00:04 End time: 00:00:12 Duration: 8 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 2

Student information:

Emotional state: Negative Cognitive state: Retrieving

PrerequisiteKP mastered?: 0.85 Student capability: 0.85

KP difficulty level: 1

Feedback information:

Cognitive Feedback tactic 1: acceptance Emotional Feedback tactic 1: enternextstep

Feedback1: “好的，让我们跳过这点。”从下段开始（数组名的含义，第 27 秒）继续播放。

Translation of feedback1: Ok, let's move to next section.(Play the video form 27")

Cognitive Feedback tactic 2: acceptance Emotional Feedback tactic 2:

Feedback2: 从下段开始（数组名的含义，第 27 秒）继续播放。

Translation of feedback2: Let's move to next section.(Play the video form 27")

Cognitive Feedback tactic 3: relief Emotional Feedback tactic 3: pause

Feedback3: 不要急，让我们重复再看一次。

Translation of feedback3: No rush, pause and think about it again.

Video information:

Begin time: 00:00:15 End time: 00:00:21 Duration: 6 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 3

Student information:

Emotional state: Positive Cognitive state: Perceiving

PrerequisiteKP mastered?: 0.85 Student capability: 0.85

KP difficulty level: 2

Feedback information:

Cognitive Feedback tactic 1: noemofeedback Emotional Feedback tactic 1: goon

Feedback1: 继续播放视频

Translation of feedback1: No emotional feedback, go on playing the video.

Cognitive Feedback tactic 2: noemofeedback Emotional Feedback tactic 2:

Feedback2: 继续播放视频

Translation of feedback2: Go on playing the video.

Cognitive Feedback tactic 3: relief Emotional Feedback tactic 3: pause

Feedback3: 放松点，再琢磨一下。

Translation of feedback3: Take it easy, pause and think about it again.

Video information:

Begin time: 00:02:24 End time: 00:02:35 Duration: 11 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 4

Student information:

Emotional state: Negative Cognitive state: Encoding

PrerequisiteKP mastered?: 0.5 Student capability: 0.85

KP difficulty level: 3

Feedback information:

Cognitive Feedback tactic 1: relief Emotional Feedback tactic 1: giveexample

Feedback1: “别着急，假设 a 数组是 float 的，则 a[i]的地址为 a+i*4。”

Translation of feedback1: No worry. For example, if the type of array a is "float", the address of element a[i] is a+i*4.

Cognitive Feedback tactic 2: relief Emotional Feedback tactic 2:

Feedback2: “假设 a 数组是 float 的，则 a[i]的地址为 a+i*4。”

Translation of feedback2: For example, if the type of array a is "float", the address of element a[i] is a+i*4.

Cognitive Feedback tactic 3: praise/ Emotional Feedback tactic 3: goon

Feedback3: 你真棒！继续播放视频。

Translation of feedback3: You are great! Go on playing the video.

Video information:

Begin time: 00:03:42 End time: 00:04:00 Duration: 18 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 5

Student information:

Emotional state: Negative Cognitive state: Perceiving

PrerequisiteKP mastered?: 0.15 Student capability: 0.85

KP difficulty level: 4

Feedback information:

Cognitive Feedback tactic 1: relief Emotional Feedback tactic 1: reviewprerequisiteKP

Feedback1: 放松点，让我们再来看看指针相关的运算符 * 和 [] 的用法。(播放上一讲中讲述指针相关的运算符 * 和 [] 的用法的片段)

Translation of feedback1: Take it easy. Let's review the usage of the pointer operator * and [] in last lecture.(Play from 14'25" to 22'41" CProgrammingZengyi25.flv)

Cognitive Feedback tactic 2: relief Emotional Feedback tactic 2:

Feedback2: 再来看看指针相关的运算符 * 和 [] 的用法。(播放上一讲中讲述指针相关的运算符 * 和 [] 的用法的片段)

Translation of feedback2: Let's review the usage of the pointer operator * and [] in last lecture.(Play from 14'25" to 22'41" CProgrammingZengyi25.flv)

Cognitive Feedback tactic 3: encouragement Emotional Feedback tactic 3: goon

Feedback3: “加油！”+继续播放视频

Translation of feedback3: Come on! Go on playing the video.

Video information:

Begin time: 00:05:03 End time: 00:05:50 Duration: 47 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 6

Student information:

Emotional state: Negative Cognitive state: Perceiving

PrerequisiteKP mastered?: 0.15 Student capability: 0.85

KP difficulty level: 4

Feedback information:

Cognitive Feedback tactic 1: relief Emotional Feedback tactic 1: reviewprerequisiteKP

Feedback1: 别急，a 表示数组的首地址，是常量，值是不能被更新的，但是变量的值可以被更新。

Translation of feedback1: No worry, let's review the meaning of the name of the array. Array's name "a" means the start address of the array. It is a constant and the value of a constant cannot be changed.

Cognitive Feedback tactic 2: relief Emotional Feedback tactic 2:

Feedback2: a 表示数组的首地址，是常量，值是不能被更新的，但是变量的值可以被更新。

Translation of feedback2: Let's review the meaning of the name of the array. Array's name "a" means the start address of the array. It is a constant and the value of a constant cannot be changed.

Cognitive Feedback tactic 3: praise/ Emotional Feedback tactic 3: goon

Feedback3: 你真棒！继续播放视频。

Translation of feedback3: You are great! Go on playing the video.

Video information:

Begin time: 00:06:29 End time: 00:07:20 Duration: 51 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 7

Student information:

Emotional state: Negative Cognitive state: Retrieving

PrerequisiteKP mastered?: 0.85 Student capability: 0.5

KP difficulty level: 2

Feedback information:

Cognitive Feedback tactic 1: encouragement Emotional Feedback tactic 1: repeat

Feedback1: 再试着想想，重复再看一次这段。（重新从 7 分 25 秒播放）

Translation of feedback1: Try to think it again. Let's repeat this part.

Cognitive Feedback tactic 2: encouragement Emotional Feedback tactic 2:

Feedback2: 重复再看一次这段。（重新从 7 分 25 秒播放）

Translation of feedback2: Let's repeat this part.

Cognitive Feedback tactic 3: encouragement Emotional Feedback tactic 3: goon

Feedback3: “加油！”+继续播放视频

Translation of feedback3: Come on! Go on playing the video.

Video information:

Begin time: 00:07:25 End time: 00:07:57 Duration: 32 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 8

Student information:

Emotional state: Negative Cognitive state: Encoding

PrerequisiteKP mastered?: 0.85 Student capability: 0.5

KP difficulty level: 4

Feedback information:

Cognitive Feedback tactic 1: encouragement Emotional Feedback tactic 1: giveexample

Feedback1: 再想想看，举个例子，当 i=1 的时候，把 a[1]的地址付给指针变量 p，依此类推。

Translation of feedback1: Try to think it again. For example, when i=1, it is assigning the address of a[1] to pointer p, and so on.

Cognitive Feedback tactic 2: encouragement Emotional Feedback tactic 2:

Feedback2: 举个例子，当 i=1 的时候，把 a[1]的地址付给指针变量 p，依此类推。

Translation of feedback2: For example, when i=1, it is assigning the address of a[1] to pointer p, and so on.

Cognitive Feedback tactic 3: praise/ Emotional Feedback tactic 3: goon

Feedback3: 你真棒！继续播放视频。

Translation of feedback3: You are great! Go on playing the video.

Video information:

Begin time: 00:09:09 End time: 00:09:28 Duration: 20 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 9

Student information:

Emotional state: Negative Cognitive state: Encoding

PrerequisiteKP mastered?: 0.5 Student capability: 0.5

KP difficulty level: 4

Feedback information:

Cognitive Feedback tactic 1: relief Emotional Feedback tactic 1: giveexample

Feedback1: 放松，比如当 i=0 时，p 指向 a[0],*p，也就是 a[0]的值被赋为 0。

Translation of feedback1: Take it easy. For example, when i=0, p points to a[0], the value of *p or a[0] is assigned by 0.

Cognitive Feedback tactic 2: relief Emotional Feedback tactic 2:

Feedback2: 比如当 i=0 时，p 指向 a[0],*p，也就是 a[0]的值被赋为 0。

Translation of feedback2: For example, when i=0, p points to a[0], the value of *p or a[0] is assigned by 0.

Cognitive Feedback tactic 3: encouragement Emotional Feedback tactic 3: goon

Feedback3: “加油！”+继续播放视频

Translation of feedback3: Come on! Go on playing the video.

Video information:

Begin time: 00:12:00 End time: 00:12:51 Duration: 50 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 10

Student information:

Emotional state: Negative Cognitive state: Retrieving

PrerequisiteKP mastered?: 0.85 Student capability: 0.85

KP difficulty level: 1

Feedback information:

Cognitive Feedback tactic 1: acceptance Emotional Feedback tactic 1: enternextstep

Feedback1: 好的，你已经懂了，让我们跳过这点。（从 14 分 7 秒开始播放）

Translation of feedback1: OK, you have understood this. Let's move to next section.(Play the video form 14'7")

Cognitive Feedback tactic 2: acceptance Emotional Feedback tactic 2:

Feedback2: 跳过这点。（从 14 分 7 秒开始播放）

Translation of feedback2: Let's move to next section.(Play the video form 14'7")

Cognitive Feedback tactic 3: relief Emotional Feedback tactic 3: pause

Feedback3: 别紧张，我们停下来仔细想想。

Translation of feedback3: Take it easy, let's pause and think about it.

Video information:

Begin time: 00:13:30 End time: 00:13:53 Duration: 23 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 11

Student information:

Emotional state: Negative Cognitive state: Perceiving

PrerequisiteKP mastered?: 0.15 Student capability: 0.5

KP difficulty level: 4

Feedback information:

Cognitive Feedback tactic 1: relief Emotional Feedback tactic 1: reviewprerequisiteKP

Feedback1: 别急，让我们复习一下如何通过指针访问数组元素。（4 分 25 秒至 6 分 20 秒）

Translation of feedback1: No worry, let's review how to access the array elements using pointer.(Play from 4'25" to 6'20")

Cognitive Feedback tactic 2: relief Emotional Feedback tactic 2:

Feedback2: 复习一下如何通过指针访问数组元素。（4 分 25 秒至 6 分 20 秒）

Translation of feedback2: Let's review how to access the array elements using pointer.(Play from 4'25" to 6'20")

Cognitive Feedback tactic 3: relief Emotional Feedback tactic 3: repeat

Feedback3: 不要急，让我们重复再看一次。

Translation of feedback3: No rush, let's repeat this part again.

Video information:

Begin time: 00:16:04 End time: 00:16:42 Duration: 38 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 12

Student information:

Emotional state: Negative Cognitive state: Encoding

PrerequisiteKP mastered?: 0.15 Student capability: 0.5

KP difficulty level: 3

Feedback information:

Cognitive Feedback tactic 1: relief Emotional Feedback tactic 1: reviewprerequisiteKP

Feedback1: 别紧张，我们之前讲过 a+i 就是表示数组元素 a[i]的地址，和&a[i]是一样的。

Translation of feedback1: Take it easy,let's review this: a+i is the address of the array element a[i], the same meaning as &a[i].

Cognitive Feedback tactic 2: relief Emotional Feedback tactic 2:

Feedback2: 之前讲过 a+i 就是表示数组元素 a[i]的地址，和&a[i]是一样的。

Translation of feedback2: Let's review this: a+i is the address of the array element a[i], the same meaning as &a[i].

Cognitive Feedback tactic 3: praise/ Emotional Feedback tactic 3: goon

Feedback3: 你真棒！继续播放视频。

Translation of feedback3: You are great! Go on playing the video.

Video information:

Begin time: 00:17:49 End time: 00:17:58 Duration: 9 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 13

Student information:

Emotional state: Negative Cognitive state: Encoding

PrerequisiteKP mastered?: 0.85 Student capability: 0.15

KP difficulty level: 3

Feedback information:

Cognitive Feedback tactic 1: encouragement Emotional Feedback tactic 1: giveexample

Feedback1: 这点你可以理解的，当 p 指向 a[5]元素的时候，是可以进行+或者-的运算的，而数组指针 a 只能指向数组的起始地址，因此只能+不能-。

Translation of feedback1: Trust yourself, you could understand this. For example, when pointer p points to a[5], the pointer can take the operation of "+" or "-". But array pointer "a" only can point to the start address of the array, and cannot take the operation of "+" or "-".

Cognitive Feedback tactic 2: encouragement Emotional Feedback tactic 2:

Feedback2: 当 p 指向 a[5]元素的时候，是可以进行+或者-的运算的，而数组指针 a 只能指向数组的起始地址，因此只能+不能-。

Translation of feedback2: For example, when pointer p points to a[5], the pointer can take the operation of "+" or "-". But array pointer "a" only can point to the start address of the array, and cannot take the operation of "+" or "-".

Cognitive Feedback tactic 3: encouragement Emotional Feedback tactic 3: goon

Feedback3: “加油！”+继续播放视频

Translation of feedback3: Come on! Go on playing the video.

Video information:

Begin time: 00:19:55 End time: 00:20:56 Duration: 61 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 14

Student information:

Emotional state: Negative Cognitive state: Encoding

PrerequisiteKP mastered?: 0.85 Student capability: 0.15

KP difficulty level: 4

Feedback information:

Cognitive Feedback tactic 1: encouragement Emotional Feedback tactic 1: repeat

Feedback1: 不要急，让我们重复再看一次。

Translation of feedback1: No rush, let's repeat this section .

Cognitive Feedback tactic 2: encouragement Emotional Feedback tactic 2:

Feedback2: 重复再看一次。

Translation of feedback2: Let's repeat this section .

Cognitive Feedback tactic 3: praise/ Emotional Feedback tactic 3: goon

Feedback3: 你真棒！继续播放视频。

Translation of feedback3: You are great! Go on playing the video.

Video information:

Begin time: 00:23:55 End time: 00:24:29 Duration: 34 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 15

Student information:

Emotional state: Positive Cognitive state: Anticipating

PrerequisiteKP mastered?: 0.5 Student capability: 0.15

KP difficulty level: 2

Feedback information:

Cognitive Feedback tactic 1: encouragement Emotional Feedback tactic 1: goon

Feedback1: 加油，让我们继续吧。

Translation of feedback1: Come on. Go on playing the video.

Cognitive Feedback tactic 2: encouragement Emotional Feedback tactic 2:

Feedback2: 继续播放。

Translation of feedback2: Go on playing the video.

Cognitive Feedback tactic 3: relief Emotional Feedback tactic 3: repeat

Feedback3: 不要急，让我们重复再看一次。

Translation of feedback3: No rush, let's repeat this part again.

Video information:

Begin time: 00:25:40 End time: 00:26:05 Duration: 25 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 16

Student information:

Emotional state: Negative Cognitive state: Encoding

PrerequisiteKP mastered?: 0.5 Student capability: 0.15

KP difficulty level: 4

Feedback information:

Cognitive Feedback tactic 1: relief Emotional Feedback tactic 1: repeat

Feedback1: 放松点，让我们重复再看一次。

Translation of feedback1: Take it easy, let's repeat this section .

Cognitive Feedback tactic 2: relief Emotional Feedback tactic 2:

Feedback2: 重复再看一次。

Translation of feedback2: Let's repeat this section .

Cognitive Feedback tactic 3: praise/ Emotional Feedback tactic 3: goon

Feedback3: 你真棒！继续播放视频。

Translation of feedback3: You are great! Go on playing the video.

Video information:

Begin time: 00:27:09 End time: 00:28:35 Duration: 26 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 17

Student information:

Emotional state: Negative Cognitive state: Encoding

PrerequisiteKP mastered?: 0.15 Student capability: 0.15

KP difficulty level: 5

Feedback information:

Cognitive Feedback tactic 1: relief Emotional Feedback tactic 1: reviewprerequisiteKP

Feedback1: 不急，回忆一下，*q++运算是先执行*运算，再执行++操作。"*q++=*p++;"是 等价于"*q=*p; q++; p++;"的

Translation of feedback1: No rush, let's review this: *q++ is operating * first, then ++. "*q++=*p++;" is equivalent to "*q=*p; q++; p++;".

Cognitive Feedback tactic 2: relief Emotional Feedback tactic 2:

Feedback2: *q++运算是先执行*运算，再执行++操作。"*q++=*p++;"是 等价于"*q=*p; q++; p++;"的

Translation of feedback2: Let's review this: *q++ is operating * first, then ++. "*q++=*p++;" is equivalent to "*q=*p; q++; p++;".

Cognitive Feedback tactic 3: encouragement Emotional Feedback tactic 3: goon

Feedback3: “加油！”+继续播放视频

Translation of feedback3: Come on! Go on playing the video.

Video information:

Begin time: 00:29:01 End time: 00:29:42 Duration: 41 seconds

Video file name: CProgrammingZengyi25.flv

Case ID: 18

Student information:

Emotional state: Negative Cognitive state: Reinforcing

PrerequisiteKP mastered?: 0.15 Student capability: 0.15

KP difficulty level: 5

Feedback information:

Cognitive Feedback tactic 1: sympathy Emotional Feedback tactic 1: explainanswer

Feedback1: 我也觉得这点不容易，解释一下是因为上个 for 循环结束的时候 q 已经是指向数组末尾即 a[9]元素之后，如果不重新让 q 指向数组的起始地址就运行*q++，那么就超出数组元素的范围了。

Translation of feedback1: I know this is difficult. Let me explain this. When last "for loop" ends, q points to the end of the array, namely after a[9]. If q is not be assiged with the start address of the arry again, and excecute *q++ next, the address where q points to is out of

Cognitive Feedback tactic 2: sympathy Emotional Feedback tactic 2:

Feedback2: 因为上个 for 循环结束的时候 q 已经是指向数组末尾即 a[9]元素之后，如果不重新让 q 指向数组的起始地址就运行*q++，那么就超出数组元素的范围了。

Translation of feedback2: When last "for loop" ends, q points to the end of the array, namely after a[9]. If q is not be assiged with the start address of the arry again, and excecute *q++ next, the address where q points to is out of the array's range.

Cognitive Feedback tactic 3: praise/ Emotional Feedback tactic 3: goon

Feedback3: 你真棒！继续播放视频。

Translation of feedback3: You are great! Go on playing the video.

Video information:

Begin time: 00:30:05 End time: 00:30:54 Duration: 49 seconds

Video file name: CProgrammingZengyi25.flv

Appendix C Publications

1. TAO, X. & NIU, Q. 2013. Using Ethnography Method to Collect Emotional Data in Affective Learning Research. International Journal of Information and Electronics Engineering, 3, 216-220.

2. XIAO-MEI, T. & QIN-ZHOU, N. 2013. An emotion classification algorithm based on the blink frequency detection and Bayesian network in affective learning. Computer Science, 40, 287-291.

3. XIAOMEI, T. & QINZHOU, N. 2015. Study of an algorithm about producing instructional feedback strategy based on an affective learning ontology. Computer Engineering & Science, 37, 320-328.

4. XIAOMEI, T. & QINZHOU, N. 2015. Study of an algorithm about producing utility optimal instructional feedback tactics based on Ontology and Influence Diagram model in Affective Computing. Application Research of Computers 32, 427-433.

5. XIAOMEI, T., QINZHOU, N., JACKSON, M. & HU, B. A theoretical framework of pedagogical agents based on psychological incentive mechanism and Artificial Psychology theory. IT in Medicine and Education, 2008. ITME 2008. IEEE International Symposium on, 2008. IEEE, 428-433.