Facial Expression Driven Mobile Learning System

Jeffrey S. Ingosan, Thelma D. Palaoag, and Josephine S. Dela Cruz

***Abstract*—Processing human facial expressions is a computer vision challenge in a mobile technology environment. On the other hand, facial expression is an effective tool in behavioral studies on learning environment. Since, mobile technologies possess educating potential for today's generation, the introduction of behavior as a consideration for mobile user opens up many opportunities for the design and development of a mobile learning system that can cater personalized learning.**

This undertaking was concerned with the enhancement of learners' learning engagement and the enrichment of learners' benefits. The mobile learning system approximates the learners' facial expressions. The facial expressions will be used to identify the learning moods that will then be used to match the appropriate learning materials and activities of the learners. These steps are done to achieve optimal experience in learning. Approximation of learners' facial expressions, learning moods, and matching of learning materials and activities to the learners are done through the use of intelligent computing techniques. In order for the stated endeavors to be achieved this undertaking considered three (3) stages of actions. Stage one focused on identifying the requirements needed to design, develop and assess the proposed facial expression driven mobile learning system. The second stage focused on the actual design and development of a prototype for the proposed facial expression driven mobile learning system and the third stage focused on the assessment of the prototype of the proposed facial expression driven mobile learning system. Assessment was done by pilot testing the mobile learning system prototype to a student sample from the researchers' locality.

***Index Terms*—Mobile learning, facial expression recognition, attention state, learning styles.**

I. Introduction

Modern human civilization is the product of education; and today, knowledge is recognized as an important asset. To improve knowledge, the process of learning plays an important role. Thus, improving the process of learning is important because of the need of people for more knowledge.

Content delivery, assessment and feedback comprise the learning process. This can be confirmed by the traditional education process. An improvement to the traditional education is the use of Computer-Assisted Learning, where the computer is utilized as a tool to deliver the content and assessment. Further, researches on the education process have paved way to mobile learning as an improvement. It is known that mobile earning is doing the learning process at one's own time and pace. This has broadened the recipients of education such as working individuals, professionals, distant students, and physically incapacitated individuals. However, these educational technologies are unsuccessful due to limited contact between the teacher and students, diversity of platform, and unsatisfactory learning content.

There are several approaches to achieve optimal learning experience. First, regulate the environment that controls the flow of learning that is used to present the learning content. Computer-Based learning, Computer-Assisted learning and eLearning could be some of the terms used to describe the environment. Second, regulate the learning content; and lastly, regulate the process to which these contents can be combined [1].

Facial expressions play an important role in human interactions and non-verbal communication. Classifying the facial expressions could be used as an effective tool in behavioural studies.

The use of technology in the delivery of knowledge to learners is seen on institutions around the world. Indeed, the use of eLearning is present both inside and outside the classroom. With the advancement of technology, mobile learning became a trend where one can learn anywhere and anytime through mobile devices. Even formal and informal learning as part of lifelong learning are taking advantage of what technology can offer.

Unfortunately, electronic learning tools are not able to recognize if students are engaged and attentive to the lesson unlike actual teachers in a traditional classroom setting. Therefore, it would be an innovation if these electronic learning tools are able to approximate the level of engagement and attention of learners through the use of facial expression recognition, attention state recognition and fuzzy logic. This is to enable the electronic learning tool to use the appropriate learning materials and activities based on the level of engagement and attention of the learner. Further, most of the e-learning systems today are adaptive to the learning styles or preferences of learners that it would be necessary to consider this in the design and development of electronic learning tools.

A. Statement of the Problems

This undertaking tried to enhance the learning engagement of learners by the use of the facial expression driven mobile learning system. Specifically, the undertaking attempted to address the following:

1) What facial expressions shall be considered to identify the learning moods of learners?
2) What shall be the use of fuzzy logic in the proposed facial expression driven mobile learning systems?
3) What classification of facial expressions, attention states, and learning materials and activities shall be in a facial expression driven mobile learning?
4) What is the difference of the learner's engagement in a

Manuscript received June 4, 2013; revised August 7, 2013.

Jeffrey S. Ingosan, Thelma D. Palaoag, and Josephine S. Dela Cruz are with the University of the Cordilleras, Philippines (e-mail: jeff_ffej2002@yahoo.com, tpalaoag@gmail.com, delacruzpen@gmail.com).

facial expression driven and a mobile learning that does not consider facial expression?

B. Research Hypothesis

A number of published research papers on the use of mobile learning systems focused on the amount of knowledge that the user of these said learning systems gained. On the other hand, this paper focused on determining the possibility of improving the engagement of a learner by using facial expression in a mobile learning environment. This paper is not concerned with the amount of knowledge that a learner can gain from using the proposed facial expression driven mobile learning system. With this in mind the researcher wanted to prove the hypothesis: There is better learner's engagement in a mobile learning environment that uses facial expression reognition.

II. METHODOLOGY

The following are the stages that the researchers had undertaken to achieve the objectives of the research.

A. Stage 1: Requirements Identification

This stage was focused on identifying the requirements needed to design, develop and assess the proposed facial expression driven mobile learning system. Review of literature was conducted to identify the appropriate facial expressions, learning moods, intelligent computing techniques, and learning materials and activities that were utilized in this undertaking. Related researches that were conducted were reviewed. Findings, recommendations, and even issues that were encountered on these related research undertakings were highly considered. By the end of this stage useful facial expressions, learning moods, intelligent computing techniques, and learning materials and activities were identified while those that were not used were determined together with a reasonable discussion on why these were not considered.

B. Stage 2: Design and Development of Facial Expression Driven Mobile Learning System

This stage focused on the actual design and development of the proposed facial expression driven mobile leaning system prototype. Design of existing mobile learning systems were reviewed by the researchers. Useful techniques were determined while difficulties and issues that were encountered by other researchers and developers were considered to guarantee a quality system output. Development was done by the researchers with the help of experts in mobile application development and used highly recommended development tools by these experts. At the end of this stage, a well documented and working facial expression driven mobile learning system prototype was delivered.

C. Stage 3: Assessment of the Facial Expression Driven Mobile Learning System

This stage focused on the assessment of the proposed facial expression driven mobile learning system prototype. In this stage 197 sample students from the researchers' locality assessed the proposed facial expression driven mobile learning system prototype. Hypothesis testing was conducted to determine if there was a significant effect on the learners' learning engagement by using the proposed mobile system prototype. Users' perceived benefits were also collected as additional basis for the assessment.

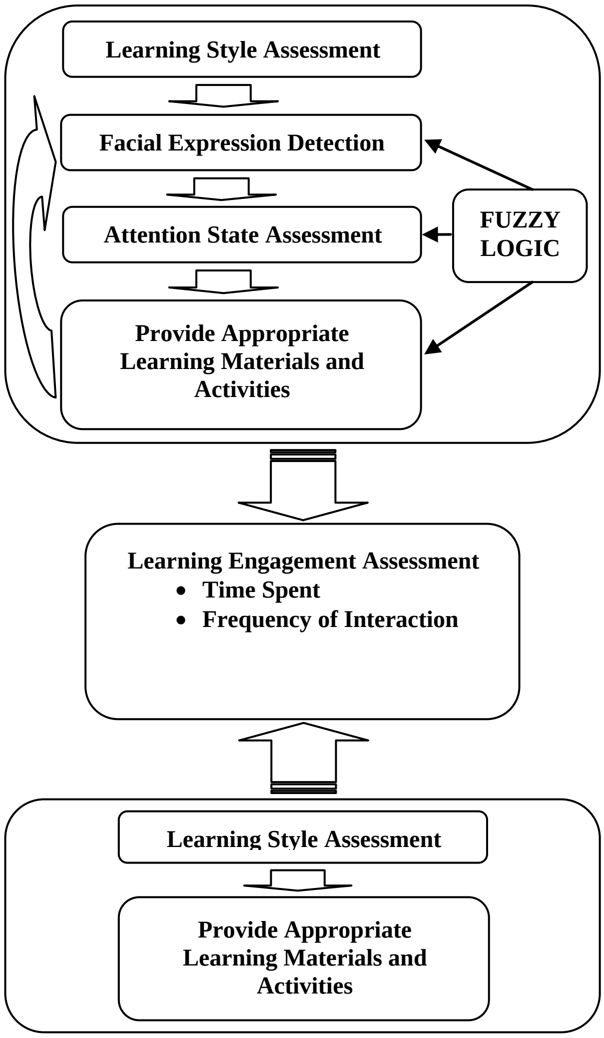

Fig. 1. Conceptual framework.

Fig. 1 illustrates the conceptual framework that was used by the researchers. The conceptual framework presents the goal of this undertaking. Two mobile learning systems were tested to show that learning engagement of a learner is better in a facial expression driven mobile learning system than in a traditional mobile learning system.

The facial expression driven mobile learning system works by initially identifying the type of learning materials and activities preferred by the learner. These learning materials and activities are categorized based on their difficulty or challenge level. The difficulty or challenge level of the learning materials and activities that are presented to the learner depend on the attention state of the learner that is further based on the learner's facial expression. During the use of the mobile learning system the learning materials and activities can be changed to a more challenging or easier learning materials to learn and activities to accomplish depending on the changes on the learner's facial expression that affect the learner's attention state. Further, the ability of the mobile learning system to identify the facial expression, attention state, and learning materials and activities are done with the use of fuzzy logic.

On the other hand, the traditional mobile learning system simply identifies the preferred learning materials and activities of the learner. The preferred learning materials and activities are presented regardless of their difficulty or challenge level. Facial expression and attention state of the learner are not determined by the mobile learning system.

The engagements of the learners during the use of the two different mobile learning systems were compared to determine if there is a better learner's engagement in a facial expression driven mobile learning system than in a traditional mobile learning system. Two factors were considered to measure the engagement of the learner. The first factor is the time spent by the learner in using the mobile learning system. The second factor is the frequency of interaction or how active is the learner in using the mobile learning systems.

III. Review of Related Literature

Artificial intelligence in education continue to integrate pedagogical model in building computerized mechanisms that will accurately, immediately and continually recognize a learner's affective state. Many emotion recognition approaches are built using facial expressions and majority of studies investigating the recognition of facial expressions have focused on static displays of intense emotions. Most of the studies that recognizes the facial expression or mood of the user did not gauge the learning engagement of the learner.

Researchers in many different fields are familiar with Ekman's work on the detection of emotions from facial expressions [2]. However, the emotions that Ekman intensely investigated (e.g., sadness, happiness, anger, fear, disgust, surprise) have minimal relevance to learning per se [3]. The pervasive affective states during complex learning include confusion, frustration, boredom, flow/engagement, interest, and being stuck [4]-[6] have proposed an efficient method for recognizing emotion from facial expressions using a robust feed-forward intelligent method, which can be applied to a color image containing the frontal view of the human face. Moreover, [7] emphasized the use of intelligent method in facial expression to improve the processing speed and normalized the images. It is a method to improve the efficiency and to increase the database of expression. In the study done by [8], they discussed the major issues in recognizing the quality and quantity of emotion databases. They considered a hybrid system that has a particular attraction that links the elements that are prominent in reactions to emotion. In addition, [9] presented the application of intelligent method based feature extraction in combination with learning vector quantization (LVQ) for recognition of seven different facial expressions from still pictures of the human faces and proved feasible on computer vision applications on facial expression recognition and human computer interaction.

According to [10], the ideal representation of emotion should not be purely descriptive: it should also concern itself with predicting and prescribing actions. It should be capable of modification through experience, as developmental and cross-cultural evidence indicate human representations. [11] stated in his study, "the act of learning needs to be pleasurable in itself (and perhaps this is more important than the final accomplishment) is to remain engaged". Part of the skill of designing a successful interactive learning is balancing these various constraints and conditions to tune the level of boredom and anxiety and keep the piece engaging. Increasing the level of engagement of learners improves learning experiences.

Authors in [12] demonstrated how various kinds of evidence could be combined to optimize inferences about affective states during an online self-assessment test. They demonstrate how formula-based and intelligent method could be combined to optimize inferences about affective states during an online self-assessment test. Their work indicates that intelligent method can provide a significant prediction of student's mood using personal preference information and can provide an alternative for and improvements over tutoring systems' affect recognition methods. Authors of [3] [12] mentioned that an appropriate computer response to a student's affective state also requires evolving and integrating new pedagogical models into computerized learning environments, which assess whether or not learning is proceeding at a healthy rate and intervene appropriately.

IV. Findings

This section presents the findings of the undertaking.

A. Facial Expressions, Attention States, and Learning Materials and Activities Classifications

Facial expressions and attention states that show positive reaction such as happiness, excitement and negative reaction such as anger, fear, disgust and sadness were used in this study. These two classifications of facial expressions and attention states were useful in determining the different states of the learner based on the learner's engagement. These negative and positive facial expressions and attention states were used to help determine whether a leaner is in an apathy, relaxation, anxiety or flow state.

Learning materials and activities for learners with different learning styles were prepared. Using the VAK Learning style model, learning materials and activities for visual learners, auditory learners and kinesthetic learners were prepared. Further learning materials and activities that require high level of skills and learning materials and activities that requires low level of skills were designed for each type of learner.

B. Fuzzy Logic

A fuzzy logic model was used to approximate the attention state of the learner based on the identified facial expression. The appropriate learning materials and activities were also identified based on the learner's attention state through the use of a fuzzy logic model.

C. Design of the Mobile Learning Systems

The facial expression driven mobile learning system determines the learning style of the learner at the start. The learning style is determined by providing a questionnaire that will classify the learner based on the VAK Model. The VAK

Self-Assessment Questionnaire, a proven VAK tool to classify learners, was used. An existing module on recognizing the facial expression and the attention state of the leaner was also used. The determined attention state is then used to identify the appropriate learning materials and activities for the learner. After providing the learning materials and activities the cycle is repeated from the process of evaluating the facial expression and attention state of the learner before the next learning material or activity is presented. Further, the system is also able to keep track of the level of difficulty of the learning materials and activities of each student.

On the other hand, an existing mobile learning system that provides learning materials and activities to the learner based on the learner's learning style but does not consider facial expression was also used in this study. The VAK Model and the VAK Self-Assessment Questionnaire were also used by this existing mobile learning system.

Both mobile learning systems are able to keep track of the time each student spent on each mobile learning system. The number of accomplished activities and accessed materials of each student are also recorded by the mobile learning system.

D. Difference of the Mobile Learning Systems

After the pilot testing of the mobile learning systems the researcher was able to gather the following data:

Table I shows the average time spent and number of learning modules and activities accessed by the students during the pilot testing of the two mobile learning systems. The table is able to show that students had longer learning engagement and were able to access and accomplish more learning materials and activities during the use of the facial expression driven mobile learning system.

Table II shows the number of students and their experiences during the use of the facial expression driven mobile learning system. The table further shows that majority of the students achieved flow during the use of the facial expression driven mobile learning system.

TABLE I: AVERAGE TIME SPENT AND NO. OF LEARNING MODULES AND ACTIVITIES ACCESSED AND ACCOMPLISHED BY THE STUDENTS

Day	Hour	Facial Expression Detection	Average Time Spent by Students	Average No. of Learning Modules & Activities Accessed & Accomplished
1st	1st	System without	45 min.	10 out of 12
1st	2nd	System with	56 min.	12 out of 12
1st	3rd	System without	43 min.	8 out of 12
1st	4th	System with	57 min.	11 out of 12
2nd	1st	System with	56 min.	11 out of 12
2nd	2nd	System without	46 min.	9 out of 12
2nd	3rd	System with	55 min.	12 out of 12
2nd	4th	System without	39 min.	6 out of 12

TABLE II: NUMBER OF STUDENTS WITH THEIR EXPERIENCES DURING THE USE OF THE FACIAL EXPRESSION DRIVEN MOBILE LEARNING SYSTEM

Day	Hour	Apathy	Relaxation	Anxiety	FLOW
1st	2nd	21	33	6	137
1st	4th	19	34	6	138
2nd	1st	20	30	7	140
2nd	3rd	17	31	5	144

Using the gathered data during the testing of the mobile learning systems, paired t-test was done to compare the engagement of the learners. The t-test resulted to a P value of less than 0.0001 that suggested the rejection of the null hypothesis and acceptance of the alternative hypothesis. The mean engagement time of students that used the facial expression driven mobile learning system is 56.10 with a standard deviation of 1.83. On the other hand, 43 is the mean engagement time for students that used the other mobile learning system with a standard deviation of 2.30.

V. DISCUSSIONS

Apathy is a state where the learner demonstrates low level of skills for activities with low challenge level. Apathy usually results to a negative facial expression and attention state. Relaxation is a state where the learner demonstrates high level of skills for activities with low challenge level. Relaxation usually results to positive facial expression and attention state. Anxiety on the other hand, is a state where the learner demonstrates low level of skills for activities with high challenge level. Anxiety usually results to a negative facial expression and attention state. Lastly, flow is a state where the learner demonstrates high level of skills for activities with high challenge level. Flow usually results to a positive facial expression and attention state. It should be noted that low level of skill means that the learners is not maximizing his abilities while a high level of skill means that the learner is maximizing his abilities. The challenge level on the other hand focuses on the difficulty of the task at hand.

Experts and published papers on optimal experience determined the importance of balancing the skills of a learner and the challenge of the learning materials and activities. It was insisted that optimal experience can be achieved by seeing to it that the level of difficulty of learning materials and activities for a learner should be able to maximize the learner's skill.

Published research papers and even experts agree that a learner's engagement can be shown in three forms. These are concentration, interest and enjoyment. The presence of these three factors can result to an active participation of the learner, such as frequent use of the mobile learning system and its features in a mobile learning environment. This can also result to the reduction or total elimination of idleness and maximization of the provided learning time. Fuzzy logic can be used to approximate the appropriate learning materials and activities for learner based on the learners facial expression and attention state.

There is a good number of existing systems that determine and process the facial expression of users of these systems. These systems are also able to recognize the attention state of the users. It was also learned that most of these facial expression recognition systems can be added and be used by other systems. It should also be noted that there is a good number of available mobile learning systems that consider the learning style of learners. These mobile learning systems determine the learning style of a learner and provide the appropriate learning materials and activities based on the learning needs of the learner.

VI. CONCLUSIONS

Bringing out the best skills of the learner and balancing it with the appropriate learning materials and activities can be done to achieve optimal experience in a mobile learning environment. It should however be noted that these learning materials and activities should correspond to the learning style of the learner. Further, it is possible to approximate the balance between learning materials and activities with the learner's skills by determining the learner's attention state through the facial expression.

Fuzzy logic can be used to create models that would determine the appropriate learning materials and activities for a learner based on the learner's facial expression and attention state.

There are existing systems that are able to recognize the facial expression and attention state of a leaner. These systems can then be used to improve other information system such as the proposed facial expression driven mobile learning system. Likewise, there also are mobile learning systems that determine the appropriate learning materials and activities for a learner. This is based on the learner's learning style but does not consider the facial expression of the learner. Therefore, these mobile learning systems that does not consider optimal experience cannot guarantee the learner's engagement.

Finally, this undertaking showed that a facial expression driven mobile learning system can significantly increase the engagement of the learner by improving the interaction of the learner to the mobile learning system and the maximization of the provided learning time.

REFERENCES

[1] D. Burgos, T. Tattersall, and R. Koper, "Representing adaptive E-learning strategies in IMS learning design," presented at the TEN Competence Conference, Sofia, Bulgaria, March 31, 2006.

[2] P. Ekman and W. V. Friesen, *The facial action coding system: A technique for the measurement of facial movement*, Palo Alto: Consulting Psychologists Press, 1978.

[3] B. Kort, R. Reilly, and R. W. Picard, "External representation of learning process and domain knowledge: Affective state as a determinate of its structure and function," in *Proc. The artificial intelligence in education workshops*, San Antonio, TX, AIED, pp. 64–69.

[4] S. D. Craig, A. C. Graesser, J. Sullins, and B. Gholson, "Affect and learning: An exploratory look into the role of affect in learning with AutoTutor," *Journal of Educational Media*, vol. 29, pp. 241-250, 2004.

[5] M. Csikszentmihalyi, S. Abuhamdeh, and J. Nakamura, *Handbook of Competence and Motivation*, New York: The Guilford Press, 2005, pp. 598–698.

[6] R. K. Sreenivasa, V. K. Saroj, S. Maity, and S. G. Koolagudi, "Recognition of emotion from video using neural network models," *Expert Syst. Appl*., vol. 38, September 2011.

[7] V. L. Praseeda and M. Sasikumar, "A neural network based facial expression analysis using gabor wavelets," *World Academy of Science, Engineering and Technology*, vol. 42, 2008.

[8] R. Cowie, E. Douglas-Cowie, and C. Cox, "Special issue: Beyond emotion archetypes: Databases for emotion modelling using neural networks," *Neural Networks-Special Issue: Emotion and Brain*, vol. 18, pp. 371-388, May 2005.

[9] S. Bashyal and G. K. Venayagamoorthy, "Recognition of facial expressions using Gabor wavelets and learning vector quantization," *Engineering Applications of Artificial Intelligence*, 2008, doi:10.1016/j.engappai.2007.11.010.

[10] N. Fragopanagos and J. G. Taylor, "2005 Special Issue: Emotion recognition in human-computer interaction. Neural Networks," *Neural Networks-Special Issue: Emotion and Brain*, vol. 18, pp. 389–405, May 2005.

[11] A. Polaine, "The flow principle in interactivity" in *Proc. Second Australasian conference on Interactivity Entertainment*, Sydney, Asutralia, 2010, pp. 151-158.

[12] N. C. Moridis and A. A. Economides, " Prediction of student's mood during an online test using formula-based and neural network-based method," *Computer Education*, vol. 53, pp. 644-652, November 2009

Jeffrey S. Ingosan is an associate professor in the Computer Science Department of the College of Informaion Technology and Computer Science of the University of the Cordilleras, Baguio City, Philippines. His e-mail address is jeff_ffej2002@yahoo.com.

Thelma D. Palaoag is an associate professor in the Information Technology Department of the College of Informaion Technology and Computer Science of the University of the Cordilleras, Baguio City, Philippines. Her e-mail address is tpalaoag@gmail.com.

Josephine S. Dela Cruz is an associate professor in the Computer Science Department of the College of Informaion Technology and Computer Science of the University of the Cordilleras, Baguio City, Philippines. Her e-mail address is delacruzpen@gmail.com.