

Chapter 33

Affect Recognition for Web 2.0 Intelligent E–Tutoring Systems: Exploration of Students’ Emotional Feedback

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ABSTRACT

This chapter describes how a machine vision approach could be utilized for tracking learning feedback information on emotions for enhanced teaching and learning with Intelligent Tutoring Systems (ITS). The chapter focuses on analyzing learners’ emotions to show how affective states account for personalization or traceability for learning feedback. The chapter achieves this goal in three ways: (1) by presenting a comprehensive review of adaptive educational learning systems, particularly inspired by machine vision approaches; (2) by proposing an affective model for monitoring learners’ emotions and engagement with educational learning systems; (3) by presenting a case-based technique as an experimental prototype for the proposed affective model, where students’ facial expressions are tracked in the course of studying a composite video lecture. Results of the experiments indicate the superiority of such emotion-aware systems over emotion-unaware ones, achieving a significant performance increment of 71.4%.

INTRODUCTION

Affects have begun to play interestingly vital roles in current emerging Intelligent Tutoring Systems (ITS) (Alexandar, Sarrafzadeh, & Hill, 2006). Since the early birth of research into E-learning Systems, online educational systems, have evolved from computer Aided Instructions, through Intelligent tutoring systems to Affective Tutoring Systems ATS (Sarrafzadeh, Dadgostar, Alexander, & Messom, 2004)

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(Shen, Wan, & Shen, 2009) (Whitehill, Bartlett, & Movellan, 2008). With the recent emergence of web 2.0 technologies, current and future educational e-learning promises becoming more learner-centered. However what still remains a fundamental challenge for a teacher, be it human or an intelligent learning system is that of determining how prefer a student wish to receive learning contents. As the learner interacts with an educational hypermedia system, affective behaviors indicating learning preferences should normally be tracked unobtrusively (Ghazal, Yusof M., & Mat Zin, 2011) (Bangert-Drown & Pyke, 2001). Interestingly, real time eLearning scenarios are most at times characterized by learner's basic modes or emotional expressions like; content, boredom, confusion or excitement (Whitehill, Bartlett, & Movellan, 2008). While for some learner's may be for fear of embarrassments, may hesitate asking questions, others at the same time are bored with the same content but feels inappropriate to seek a 'speed up' (Aleven & Koedinger, 2000). On the other hand even when an ITS initiates such demands (e.g. speed up), the promptness of feedbacks received is not guarantee to assists a difficulty (Whitehill, Bartlett, & Movellan, 2008). These and related developments have spawned recent emergence of Affective Tutoring System (ATSs) (Sarrafzadeh, Dadgostar, Alexander, & Messom, 2004) (Shen, Wan, & Shen, 2009) (Whitehill, et al., 2011) subfield of research. ATSs (Sarrafzadeh, Dadgostar, Alexander, & Messom, 2004) (Whitehill, et al., 2011), defines a new domain of Intelligent Tutoring systems which incorporates certain techniques inspired by field of pattern recognition or machine vision. If only student's feedbacks are tracked consciously or unconsciously, side by side, on each occurrence during learning, then such could be useful for an ATS (Alexandar, Sarrafzadeh, & Hill, 2006), to utilize and adapt according to an expressed state of the student learner in like manner as real affective human tutors do (Alexandar, Sarrafzadeh, & Hill, 2006) (Sarrafzadeh, Dadgostar, Alexander, & Messom, 2004) (de Vicente, 2003). For instance an ATS (Alexandar, Sarrafzadeh, & Hill, 2006), could dynamically adjusts its content and speed given an 'expression' of student's affect pertaining to either a "high or low" level understanding or both (Whitehill, et al., 2011).

Inspired by the above notions, a significant research effort is now focused on designing more interactive tutoring systems. Majority of such attempts lay more emphasis on realization of student's affective feedbacks only within the student module of an entire ATS architecture (Chaffar & Frason, 2004) (Robinson, McQuiggan, & Lester, 2009). A handful of such implementations exists for detecting learning frustration, stress or in general, emotions (Winslow, B; Massachusetts Institute of Technology Department of Architecture Program In Media Arts and Science, 2006)(McQuiggan, Lee, J., & Lester, 2007), diagnosing student's motivations and adapting to their self-efficacy (Robinson, McQuiggan, & Lester, 2009). Such self-checked activities tracks learner's emotional behaviors as major forms of affective feedbacks needed to make adjustments in the course of learning. In other words, collecting data concerning teaching and learning as they occur concurrently helps designers of educational content improve on them. Advancing techniques that tracks student's affective states inform of emotions for a conducive learning has been the motivation for recent works (Alexandar, Sarrafzadeh, & Hill, 2006) (de Vicente, 2003) (Chaffar & Frason, 2004) (Ammar, Neji, & Alimi, 2005) (D'Mello, Graesser, & Picardi, 2007 (Kort, Reilly, & Picard, 2001) (Yan-Wen, Liu, & Wang, 2008). More recently, Affective Computing (Whitehill, et al., 2011) have begun to use relevant technologies, especially for the tasks of recognizing and predicting human emotions and behaviors (Whitehill, Bartlett, & Movellan, 2008). The chapter explores such research effort been extended to domains of ATS (Alexandar, Sarrafzadeh, & Hill, 2006) (Sarrafzadeh, Dadgostar, Alexander, & Messom, 2004) (Whitehill, et al., 2011). A major concentration lies on such approaches or proposals demonstrating enhancement of the student's models of an ATS (Alexandar, Sarrafzadeh, & Hill, 2006). These includes techniques to detect non-verbal expressive behaviors (emo-

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