Modelling Affect in Learning Environments

Motivation and Methods

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***Abstract*— Emotions have a functional relevance to learning and achievement. Not surprisingly then, affective diagnoses are an important aspect of expert human mentoring. Computer-based learning environments aim to model such social dynamics to make learning with computers more immersive, engaging and hence, more effective. This paper draws on the recent surge of interest in studying emotions in learning, highlights available techniques for measuring emotions and surveys recent efforts to automatically measure emotional experience in learning environments. Finally, a context-sensitive dataset is used to develop an automatic system for modeling six pertinent emotions. This paper attempts to bring together the motivation, methodological issues, and modeling approaches for affect inference in learning environments in order to contribute to an understanding of the problem and the current state-of-art.**

Keywords - Emotion, Affective Computing, Computer-based Learning

I. INTRODUCTION

Effective tutoring by humans is an interactive and guided process where learner engagement is constantly monitored to provide remedial feedback and to maximize the motivation to learn [1]. Indeed, formative assessment and feedback is an important aspect of effectively designed learning environments and should occur continuously and unobtrusively, as part of the instruction [2]. In naturalistic settings the availability of several channels of communication facilitates the constant monitoring necessary for such an interactive and flexible learning experience [3, 4]. One of the biggest challenges for computer tutors then is to achieve the mentoring capability of expert human teachers [5]. To give such a capability to a machine tutor entails giving it the ability to infer affect. This idea of incorporating emotional intelligence in computers has motivated efforts towards automatic perception of affect. It reflects the growing understanding of the centrality of emotion in the teaching-learning process and the fact that as yet this crucial link has not been addressed in machine-learner interactions.

Building on a discussion of recent studies highlighting the relevance of emotions in learning (Section II), different techniques for measuring emotions and efforts in automatic recognition and/or prediction of affect in learning contexts are described (Sections III and IV). This is not attempted to be an exhaustive survey of the past work but a selected discussion of recent works highlighting the concern and those attempting to address it. Throughout this paper the terms emotion, affect and learner states will be used interchangeably.

II. MOTIVATION - EMOTIONS AND LEARNING

The neurobiology of emotions suggests that not only are learning, attention, memory, and social functioning, affected by, and in fact, subsumed within emotional processes, but also that our repertoire of behavioral and cognitive options has an emotional basis. This relationship underscores the importance of the ability to perceive and incorporate social feedback in learning [6]. Indeed, recent evidence from educational research supports the relationship of emotion with cognitive, motivational and behavioral processes [7]. The seminal works of Boekaerts [8], Pekrun et al [9] and Turner, Husman & Schallert [10] have pioneered the renewed surge of interest in affect and learning in educational research.

In a series of qualitative case-studies, Pekrun et al [9] demonstrated that learners experience a rich diversity of positive and negative emotions; the most frequently reported being: anxiety, enjoyment, hope, pride, and relief, as well as anger, boredom and shame. With the help of an Academic Emotions Questionnaire (AEQ) they studied the effects of these emotions on learning and achievement with cognitive and motivational mechanisms like motivation to learn, strategies of learning, cognitive resources, and self-regulation. Using dimensions of valence (positive vs. negative) and activation they distinguished four groups of emotions with reference to their performance effects – positive activating emotions (such as enjoyment of learning, hope, or pride); positive deactivating emotions (e.g., relief, relaxation after success, contentment); negative activating emotions (such as anger, anxiety, and shame); and negative deactivating emotions (e.g., boredom, hopelessness).

To evaluate the dynamic and interactive effects of affect and motivation on learning processes like task engagement and appraisal, Boekaerts [8] conducted several longitudinal studies using the On-line Motivation Questionnaire and proposes two separate, parallel processing pathways. The *cold cognition pathway* consists of meaning-generating processes that are the building blocks of learning comprehension and problem-solving. The *hot cognition* *pathway* comprises of the emotional evaluations of learning opportunities that are triggered by emotions and moods in the actual learning episode. They assert that the evaluative information of the hot cognition path is situation specific and initiates concern-related monitoring, thereby influencing both decision-making (short-term effect) as well as value attribution (long-term effect).

Based on a decade of research on motivation and a diverse study of learner-teacher interactions, Meyer and Turner [11] discovered the inseparability of emotion, motivation and cognition; and stress for integrated approaches to treat these as equal components in the social process of learning. They report their findings as *serendipitous*, to emphasize the presence of emotion in instructional interactions.

Kort, Reilly & Picard [12] propose a spiral model that combines the phases of learning using emotion axes. The horizontal emotion axes range from negative to positive across different emotion sets like anxiety-confidence, boredom-fascination, frustration-euphoria, dispirited-encouraged and terror-enchantment. The vertical axis is the learning axis representing the transition between constructive learning and un-learning. This model assumes that the learning experience involves a range of emotions in the space of the learning task and visualizes the movement of a learner from one quadrant to another.

In a bid to understand the emotional dimension of learning, O'Regan [13] explored the *lived experience* of students learning online. The study identifies both positive and negative emotions experienced by students, significantly - frustration, fear/anxiety, shame/embarrassment, enthusiasm/excitement and pride. These had a variable effect on the learning process depending on the strength and nature of the emotion, as well as the learning context.

Using a manual affect coding system, Craig et al [14] observed the occurrence of six affect states during learning with an intelligent tutoring system. They analyzed frustration, boredom, flow, confusion, eureka and neutral and found significant relationships between learning and the affective states of boredom, flow and confusion.

More recently, Jarvenoja and Jarvela [15] and Wosnitza and Volet [16] provide empirical evidence from participants in social online learning to categorize sources of emotional experience along self, task, context or social directedness to highlight the impact of students' emotions on their motivation and engagement in the learning process.

In essence, learning has a strong affective quality that impacts overall performance, memory, attention, decision-making and attitude [3, 17]. We know from a multitude of studies in different educational contexts, that learners experience a wide range of positive and negative emotions. These emotions are situated and have social and instructional antecedents. For the discourse to be effective, it is imperative then to have access to and ensure the emotional well-being of learners. Computer-based learning environments have long ignored this aspect and have concentrated mostly on modeling the behavior of a learner in response to a particular instructional strategy [18]. Since learning with computers is essentially self-paced, assessing the learner's experience becomes important. Detection of learner's affective states can be helpful not only in adapting the tutorial interaction and strategy, but also in contributing to an understanding of emotional behavior and its relation to learning, thereby facilitating an optimal learning experience.

III. MEASURING EMOTIONS

Current methods for measuring emotions can be broadly categorized as Subjective/Objective and Qualitative/Quantitative. An additional categorization as Snapshot / Continuous can be based on the timing of the measurement [16]. Snapshot type measurements are done immediately before/after the learning process while continuous measurements are process-oriented and give access to dynamic emotional experience. Table 1 lists some common emotion measurement techniques along these categories. Ideally, we require a quantitative and continuous account of emotional experience in an objective and unobtrusive manner. Space limits comparison of the relative conceptual and measurement value of each method here but it should be emphasized that physiology - in the lower-right quadrant, offers a reasonable fit to our requirements. Analyses of tutoring sessions have in fact revealed that affective diagnoses depend heavily on inferences drawn from facial expressions, body language, intonation, and paralinguistic cues [19]. Advances in the field of Affective Computing [20] have opened the possibility of emotion recognition from its nonverbal manifestations like facial expressions, body, voice and physiology. The interested reader is referred to Zeng et al [21] for a survey of affect recognition methods using audio-visual modalities. It should be understood that affect modeling in real-time is a challenging task given the complexity of emotions, their personal and subjective nature, the variability of their expression across, and even within individuals, and frequently, lack of sufficient differentiation among associated visible and measurable signals [22]. The field is promising, yet in a formative stage as current technologies need to be validated for reliability outside controlled experimental conditions.

TABLE I. METHODS FOR MEASURING EMOTIONAL EXPERIENCE

	Snapshot (Before / After Learning)		*Continuous (During Learning)*	
	Qualitative	*Quantitative*	*Qualitative*	*Quantitative*
Subj.	Open Interviews Emotional Probes Stimulated Recall	Questionnaires Surveys	Emotional Diaries Think-aloud	Experience / Time-Sampling
Obj.	Structured Interviews	Transcripts VideoAnalyses	Observational Analyses	Interactional Content Analyses **Physiology**

IV. AUTOMATIC MEASUREMENT OF AFFECT

A. Prior Work

Machine perception of affect is a challenging problem given the inherent difficulty in conceptualizing affect and the technical constraints in access, measurement and fusion of emotional signals from the verbal and nonverbal channels. Table II compares previous work in affect sensing in learning environments to emphasize the range in the affect constructs measured, the information sources used, the learning contexts in which the study was done and the specific computational approach adopted. However, lack of common evaluative criteria makes a straightforward comparison difficult. The nature and dynamics of emotions in a solo learning setting will no doubt differ from those generated within an agent-based learning environment or with those that involves dialogue. This makes it difficult to comment on the overall performance and generalization ability of a system and is an acknowledged limitation of affect sensing technologies in general. Hence, the merit of these methods has yet to be established satisfactorily, a discussion of which is beyond the scope of this paper.

B. *Proposed System*

To contribute to the efforts listed in Table II we describe a fully automatic parallel inference system designed to continuously and unobtrusively model emotions in real-time. The emotion *groups* considered are bored, confused, happy, interested, neutral and surprised. These are selected for their relevance to learning and are derived using a taxonomy of complex mental states by Baron-Cohen [23] that groups together semantically similar emotion concepts. Confusion for example includes states like unsure, puzzled, baffled and clueless while Happy includes pleased, cheerful, relaxed, calm, enjoying, etc. These emotion descriptors thus have a wider scope than considered by previous methods.

1) *Choice of Modality*

Lack of a consistent mapping between observable aspects of behavior and actual affective states, technical feasibility, and practical issues complicate the choice of modality for sensing in a learning setting. Issues of ethics, privacy and comfort further constrain the design, use and deployment of appropriate sensing technologies. Given the pre-eminence of facial signs in human communication the face is a natural choice for inferring affective states [3]. With the latest computer vision techniques facial information can be detected and analyzed unobtrusively and automatically in real-time requiring no specialized equipment except a simple video capture device. This makes facial affect analysis an attractive choice for evaluating learner states and together with head gestures is selected as the modality for affect inference in our system.

TABLE II. AUTOMATIC RECOGNITION OF AFFECT IN LEARNING ENVIRONMENTS

Reference	Affect Concept	Information Source	Learning Context	Method
Whitehall, Bartlett & Movellan ’08 [24]	Difficulty level and speed of content	Facial expressions	Lecture videos	Support Vector Machines and Gabor filters
Zakharov, Mitrovic & Johnston ’08 [25]	Positive and negative valence	Facial expressions	Pedagogical agent-based educational environment	Rule-based system
Jacques & Vicari ‘07 [26]	OCC Cognitive Theory of Emotions [27]	User’s actions & interaction patterns	Pedagogical agent-based educational environment	Belief-Desire-Intention (BDI) reasoning; appraisal based inference
D’Mello, Picard & Graesser ‘07 [28]	Flow, Confusion, Boredom, Frustration, Eureka & Neutral	Posture, dialogue and task information	Dialogue based ITS-Auto Tutor	Comparison of multiple classifiers
Kapoor, Burleson & Picard ’07 [29]	Pre-frustration & Not pre-frustration	Facial expressions, posture, mouse pressure, skin conductance, task state	Automated Learning Companion	Gaussian process classification; Bayesian inference
Mavrikis, Maciocia & Lee ’07 [30]	Frustration, Confusion, Boredom; Confidence, Interest &Effort	Interaction logs & situational factors	Interactive Learning Environment- WALLIS	Rule induction
Amershi, Conati & Maclaren ’06 [31]	Affective reactions to game events	Skin conductance, heart rate, EMG	Educational game-Prime Climb	Unsupervised clustering
Kapoor & Picard ‘05 [32]	Interest, Disinterest, Break-taking behaviour	Facial expressions, posture patterns & task state	Educational Puzzle	Ensemble of classifiers
Heylen et al ’05 [33]	Scherer’s Component Process Model [34]	Facial expressions, task state	Agent-based ITS for nurse education-INES	Appraisal using stimulus evaluation checks
Sarrafzadeh et al ’04 [35]	Happiness/Success, Surprise/Happiness, Sadness/Disappointment, Confusion, & Frustration/Anger	Facial expressions	Elementary Maths ITS	Fuzzy-rule based classification
Litman & Forbes ’03 [36]	Negative, Neutral & Positive emotions	Acoustic-prosodic cues, discourse markers	Physics Intelligent Tutoring Dialogue System–ITSPOKE	Comparison of multiple classifiers
Conati ’02 [37]; Conati & Zhou ’02 [38]	OCC Cognitive Theory of Emotions [27]	Interaction patterns, personality, goals	Educational game-Prime Climb	Dynamic decision network; Appraisal based inference
de Vicente and Pain ’02, ‘98 [4,39]	Motivation	User actions & interaction patterns; Experience sampling	Japanese numbers ITS-MOODS	Motivation Diagnosis Rules

2) Context and Corpora

For a meaningful interpretation and to ensure ecological validity, it is essential to study the occurrence and nature of affect displays *in situ*, as they occur. Although a number of face databases exist, these are mostly posed or recorded in scripted situations that may not be entirely relevant in a learning situation. As such, a data collection exercise was undertaken in which eight participants were video-recorded while doing two computer-based learning tasks. About four hours of data was collected which underwent three annotation levels to finally get samples of the six emotion groups. This dataset is used as the ground-truth for the inference models. A detailed description of the data collection and annotation process appears elsewhere in [40].

3) Representation and Measurement of Facial Motion

The 2D face model (see Fig. 1) of the Nevenvision FaceTracker[1] is used to characterize the facial motion. This FaceTracker is a state-of-art facial feature point tracking technology and requires no manual pre-processing or calibration. It is resilient to limited out-of-plane motion, can deal with a wide range of physiognomies and can also track faces with glasses or facial hair. The FaceTracker uses a generic face template to capture the movement of 22 facial feature points over the video sequences. The displacement of these feature points over successive frames encodes the motion pattern of the face AUs [41] in a feature vector. To remove the effects of variation in face scale and projection, the distance measurements are normalized with respect to a positional line connecting the inner eyes in the first frame.

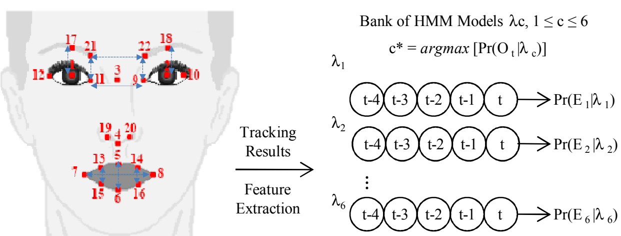

Figure 1. Feature point measurements fed to the bank of HMMs

4) Discriminative HMMs

HMMs are a popular statistical tool for modeling and recognition of sequential data [42]. We use continuous HMMs in a discriminatory manner which implies learning one HMM per class, running all HMMs in parallel and choosing the model with the highest likelihood as the most likely classification for a sequence [43, 44]. This way an HMM models the temporal signature of each emotion class so that the likelihood that an unseen sequence is emitted by each of the models can be estimated and be classified as belonging to the model most likely to have produced it.

Thus, a bank of HMMs is learned using the Baum-Welch algorithm [42] over the sample sequences. During training, the Gaussian mixtures with diagonal covariance are used and the initial estimates of state means and covariance matrices are found by k-means clustering. For classification, all HMMs are run in parallel and the forward-backward procedure [42] is used to select the model with the highest likelihood as the true class. See Fig. 1 for illustration. The observation vector for the HMMs consists of the position and speed parameters sampled over a sliding-window of five frames. This results in a multi-dimensional feature vector characterizing a filtered pattern sequence of the temporally evolving facial and head motions. PCA is used to extract salient features and reduce dimensionality.

[1] http://www.nevenvision.com: Licensed from Google Inc.

5) Results

The overall classification accuracy is estimated by averaging the true positive rate using tenfold cross-validation. To determine the best performance empirically, recognition accuracies are computed by varying the free parameters - the number of states and the number of Gaussian mixtures. Table III shows the detailed confusion matrix for the best classification achieved. Overall, for a mean false positive rate of just 1.01% the best average accuracy of 94.96% is obtained with eleven states and four Gaussian mixtures. Happy and surprised attain perfect true positive rates while others show satisfactory recognition. Individual classes attain optimal performance at varying number of states and mixtures suggesting that individual emotions have their own temporal signatures and can be modeled by aligning them along their optimal topologies. This, along with an assessment of the generalization ability, needs to be determined in future work as it requires evaluation of the system on a database that is comparable at least in terms of context and recording conditions.

TABLE III. CONFUSION MATRIX OF BEST PERFORMING HMMS

class[a]	**b**	**c**	**h**	**i**	**n**	**s**	*total*	**TP%**
b	15	1	0	0	0	0	16	93.75
c	0	57	1	0	0	1	59	96.61
h	0	0	32	0	0	0	32	100.00
i	0	4	0	27	0	0	31	87.10
n	0	0	1	0	24	1	26	92.31
s	0	0	0	0	0	32	32	100.00
total	15	62	34	27	24	34	196	**94.96**
FP%	0.00	3.65	1.22	0.00	0.00	1.22	**1.01**	

a. where b-bored, c-confusion, h-happy, i-interested, n-neutral s-surprised

V. SUMMARY AND CONCLUSIONS

A consistent theme that emerges from education literature is that teaching and learning are essentially emotional practices. Learners experience a wide range of emotions and these influence their cognitive functioning and performance. Access to emotions is then important to ensure optimal learning, more so in the case of computer-based learning environments. Nonverbal behavior is well-suited to the continuous and unobtrusive assessment of emotions as envisaged for an ideal affective computer tutor. This paper describes such a system designed to model multiple emotions simultaneously in real-time using automatic facial feature point tracking. It is build using a context-based corpus and will be optimized in future work on dataset(s) from potential learning contexts.

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