Measuring Learners' Co-Occurring Emotional Responses during Their Interaction with a Pedagogical Agent in MetaTutor

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Abstract. This paper extends upon traditional emotional measurement frameworks used by ITSs in which emotions are analyzed as single, discrete psychological experiences by examining co-occurring emotions (COEs) (e.g., Conati) through a novel methodological approach. In this paper we examined the occurrence of students' embodiment of basic single discrete emotions (SDEs) and COEs (in addition to neutral) using an automatic facial expression recognition program, FaceReader 4.0. This analysis focuses on the sub goal setting task of learners' (N = 50) interaction with MetaTutor, during which a pedagogical agent assisted students to set three relevant sub goals for their learning session. Results indicated that neutral and sadness were the SDEs experienced most by students and also the most represented emotions in COE pairs. COEs represented nearly a quarter of students' embodied emotions.

Keywords: Emotions, affect, intelligent tutoring systems, pedagogical agents, co-occurring emotions, learning, human-computer interaction, co-adaptation.

1 Co-Occurring Emotions during Learning with ITSs

Effective learning and students' experience of emotions are deeply intertwined in a variety of learning contexts [1-3]. Researchers' shared understanding of this educational tenet and its application to designing computer-based learning environments has had important implications for the development of ITSs, specifically, the development of ITSs that are able to detect, model, and adapt to changes in learners' emotional fluctuations. This paper extends upon this work by measuring learners' experience of co-occurring emotions (COEs). COEs are emotional states that occur simultaneously, where their discrete characteristics (e.g., valence, intensity) are maintained, but they are experienced in tangent with other emotional states (e.g., happiness and surprise). It is crucial that we are able to detect, measure and adapt to students' COEs during their interactions with ITSs because there are meaningful differences between a student's experience of a single discrete emotion (SDE) (e.g., anger) in comparison to the same student's experience of a pair of SDEs (e.g., anger and surprise).

In our review of the literature we found only one ITS system which considered co-occurring emotions [4], as opposed to only considering and measuring emotions as

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discrete, non-overlapping states (i.e., SDEs) [1,3,5]. A review of theories of emotions revealed only two references to COEs; neither discussed COEs as a major theoretical component [6-7]. These examples suggest that COEs have both a theoretical and methodological basis for existing and being measured and that their absence in ITS literature and other emotions literature is a shortcoming, also stated by [4].

The purpose of this paper is to examine the occurrence of COEs using a novel trace data methodology, in which learners' emotions are measured with an automatic facial recognition program, FaceReader [8]. In this paper learners' emotions were measured while they interacted with a pedagogical agent (PA) during the sub goal setting task of their interaction with MetaTutor [9]. Our research questions included: (1) what proportion of all emotions that learners' embodied, during the sub goal setting task, are COEs vs. SDEs? and (2) which pairs of COEs are most prominent?

2 Methods

2.1 Participants

50 undergraduate students from two large, public universities in North America participated in this study. Participants (74% female, 68% Caucasian) were randomly assigned to either a control condition or a prompt and feedback condition.

2.2 MetaTutor and Apparatus

MetaTutor is a multi-agent ITS and hypermedia-learning environment which consists of 41 pages of text and static diagrams about the human circulatory system [9]. The sub goal setting task, part of the sub goal setting phase of learners' interaction with MetaTutor, is the focus of our study and ranged between 1m09s and 6m03s (M = 2m22s, SD = 1m10s). This difference in time is due to participants' varying abilities to set three sub goals for learning as much as they could about the circulatory system at an appropriate level of detail, as well as the PA's scaffolding strategy.

A Microsoft LifeCam™ webcam was used to record participants' faces during their interaction with MetaTutor. The camera was mounted above the monitor and videos were recorded as WMV files, with a frame rate varying from 20 to 60 frames per second. In order to classify the embodiment of learners' emotions, we used Noldus FaceReader™ 4.0, a software program that analyzes participants' facial expressions and provides a classification of their emotional states using: (1) an Active Appearance Model to model their faces and (2) an artificial neural network with seven outputs corresponding to Ekman and Friesen's 6 basic emotions [10] in addition to neutral. Imported face videos were analyzed using FaceReader's pre-calibration and general model settings. FaceReader has been validated through comparison with human coders' ratings of basic emotions and specified acted emotions [11- 12].

2.3 Data Analysis

FaceReader provides a score between 0 and 1, for each frame of each participant's video for each of Ekman's six basic emotions, in addition to neutral. FaceReader also provides information about the dominant emotional state (computed with a proprietary algorithm using the scores of the seven emotional states in the previous frames) and timestamp information regarding the on and offset of the hierarchical rankings of these states. In order to be able to compare the results obtained to FaceReader's default proprietary algorithm, we replicated it as closely as possible in order to evaluate (for every frame) not only the primary emotional state, but also the secondary one (when it existed), using the following steps:

- First, we calculated a list of emotions, whose scores were above a minimal threshold value of 0.01 for more than 0.5s, while not disappearing completely (either because no face could be found in the frame or because their score was below 0.01) for more than 1s. The score associated with each selected emotion was either the one given by FaceReader for that frame, if available (i.e., if a face had been found in the frame), or the previous frame's score for that emotion.
- To order the emotions of the previous list, and to avoid a sequence of quick alternations from one frame to another between two emotions with very close scores, we calculated the primary (resp. secondary) emotional state as the one having the highest (resp. second highest) mean score over the past 0.5s.
- If the score of the secondary emotional state deviated no more than 0.15 from the score of the primary emotional state, we identified the emotional state of the considered frame as being a co-occurring emotional state.

Using this method, for the sample of 50 participants considered, we obtained a 91% level of agreement between the primary emotional state calculated by FaceReader and the one we calculated (97% if we also considered the value of the secondary state). In order to aggregate the data from participants, since each of the 50 videos had been recorded with a different frame rate, we normalized the sum of each emotion or pair of emotions using the frame rate value for the video. We also normalized the sum of each emotion or pair of emotions displayed in Table 1 (hence all participants have the same weight, regardless of the time spent to set sub goals). In total this analysis examined 224,582 judgments of emotional states made by FaceReader across participants.

3 Results

3.1 What Proportion of All Emotions that Learners' Embodied during the Sub Goal Setting Task Are COEs vs. SDEs?

When looking at all the possible embodiments of emotions, both SDEs and all possible pairs of COEs (see Table 1), we see that the discrete state of neutral was the emotional state with the greatest proportion (30.77%), followed by the discrete states of sadness (18.25%), happiness (10.73%) and disgust (9.33%). These four SDEs made up 69.08% of all the possible embodiments of emotions, which increased to approximately 77% of the emotions when the SDEs scared (2.00%), anger (3.22%) and surprise (2.77%) are included. The remaining 23% are different combinations of COEs.

3.2 Which Pairs of COEs Are Most Prominent?

Summing each of the different basic COEs in addition to neutral revealed that 12.45% of emotional states involved the emotion neutral co-occurring with other emotional states, 12.64% involved sadness, 7.19% involved disgust, 5.74% involved happiness, 4.34% involved anger, 2.52% involved surprise, and 1.00% involved scared. These proportions exceed 23% because of the overlapping nature of co-occurring emotions. By looking at column 5 of Table 1, we can see that the co-occurring emotional pairs which learners experienced most often included: neutral and sad (4.77%), sad and disgusted (2.99%), happy and sad (2.40%), and neutral and disgusted (2.39%). These emotional states had a greater proportion of co-occurrence than several of the single, discrete emotional states, including scared and surprised.

Table 1. Proportions of Learners'‘ SDE and COEs during the Sub Goal Setting Task

Emotion		Co-occurrence of emotions (in %)				Number of subjects embodying			
A	B	A&B	B&A	A&B or B&A	Difference A&B vs. B&A	A&B	B&A	A&B or B&A	A&B and B&A
Neutral	-	30.77	-	30.77	-	49	-	49	-
Happy	-	10.73	-	10.73	-	41	-	41	-
Sad	-	18.25	-	18.25	-	48	-	48	-
Angry	-	3.22	-	3.22	-	33	-	33	-
Surprised	-	2.77	-	2.77	-	24	-	24	-
Scared	-	1.99	-	1.99	-	14	-	14	-
Disgusted	-	9.33	-	9.33	-	39	-	39	-
Neutral	Happy	0.89	0.91	1.80	-0.02	32	29	34	27
Neutral	Sad	2.27	2.50	**4.77**	**-0.24**	43	46	46	43
Neutral	Angry	1.00	0.64	1.64	**0.35**	30	24	32	22
Neutral	Surprised	0.93	0.54	1.46	**0.39**	19	15	21	13
Neutral	Scared	0.21	0.18	0.39	0.03	13	8	14	7
Neutral	Disgusted	1.25	1.13	**2.39**	0.12	31	26	32	25
Happy	Sad	1.38	1.02	**2.40**	**0.37**	29	27	34	22
Happy	Angry	0.10	0.07	0.17	0.04	12	11	14	9
Happy	Surprised	0.11	0.12	0.23	-0.01	9	7	11	5
Happy	Scared	0.09	0.11	0.21	-0.02	8	7	12	3
Happy	Disgusted	0.45	0.48	0.93	-0.03	20	22	24	18
Sad	Angry	1.13	0.72	1.85	**0.41**	25	19	28	16
Sad	Surprised	0.27	0.12	0.39	0.16	14	11	15	10
Sad	Scared	0.14	0.11	0.25	0.03	10	8	11	7
Sad	Disgusted	1.47	1.51	**2.99**	**-0.04**	30	32	35	27
Angry	Surprised	0.02	0.07	0.09	-0.06	4	5	5	4
Angry	Scared	0.02	0.02	0.04	0.00	4	3	4	3
Angry	Disgusted	0.29	0.27	0.56	0.01	14	15	17	12
Surprised	Scared	0.05	0.02	0.07	0.02	5	4	6	3
Surprised	Disgusted	0.13	0.16	0.28	-0.03	10	9	11	8
Scared	Disgusted	0.02	0.02	0.04	-0.01	4	3	4	3

Note: The seven SDEs in lines 3 to 9 of column 1 are ordered arbitrarily. All subsequent emotions in columns 1 and 2 follow the same repeating order as the first seven until all possible pairs of emotions (i.e., COEs) have been exhausted. Columns 3 and 4 represent the proportions for which the emotions in columns 1 and 2 were the dominant emotion when paired together. Column 5 represents the proportions of co-occurring emotions pairs (sum of column 3 and 4).

4 Discussion, Conclusions and Future Directions

Our results provide us with the means to draw several interesting tentative conclusions about an important component of the psychological process of emotions that we know little about. First, that COEs, while not representing a majority of the emotional states experienced, do represent a sizeable portion, which reinforces the need to study and understand them. Second, we see that learners' proportional experience of COEs are similar to their experience of SDEs (i.e., sadness and neutral are common components in the most common pairings). Third, this paper highlights the prominence of learners' experience of neutral and sadness during the sub goal setting task of their learning session with MetaTutor. It is possible that learners experienced sadness in response to their proposed sub goals being rejected by the PA, especially since the great majority of learners failed to set their sub goals independently. In noting the prominence of learners' embodiment of neutral, it is important to remember that it is a commonly over-looked emotional state by researchers who measure emotions [1-3,10]. In this analysis, we operationalized neutral as a psychological state in which participants are not experiencing one of the six basic emotions or a positive or negative valence. The purpose of investigating learners' experiences of a neutral state is to measure their baseline state, which allows one to measure fluctuations in emotions. Neutral has a particularly important role to play in examining learners' emotional responses in ITSs as it is not necessarily realistic to expect the average undergraduate student to be in a positively-valenced emotional state (e.g., happiness, engagement) throughout the session. In these cases, neutral may be a signal that learners are in an emotional state where they are not emotionally distracted and can therefore learn (an important bottom line).

This paper represents our first exploration of a complex, but important addition to the psychological process of emotions and how it applies to MetaTutor and may apply to other ITSs and contexts. Future directions include using multiple channels to measure SDEs and COEs, including self-reports and physiological sensors, in order to cross-validate our findings. This is an important next step because our current method for detecting co-occurring emotions is data-driven and relies only on one channel, which excludes learner-centered emotions (e.g., curiosity and boredom). We are also interested in looking, not only at the alignment of SDEs and COEs with events, but at the fluctuations between various SDEs and COEs. This is an especially important direction because it will help further our understanding regarding the nature of co-occurring emotions as complex psychological processes.

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