Unobtrusive Mood Assessment for Training Applications

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Abstract

Many tasks are conducted under time and performance constraints, but the mood-congruency of real situations rarely translate to training environments. The ability to perceive affect (emotion and mood states) is essential in understanding how the trainee is reacting to the scenario. This affective data can be used to modify the challenge and flow of scenario or the amount/frequency of support/direction provided to the trainee. Today, training systems often fail to consider trainee data beyond performance measures and at times miss the opportunity to match mood stimulus in the scenario to learning needs of the trainee. This paper discusses our early results using commodity devices (e.g. Emotiv) to identify mood (a state lasting from several minutes up to several hours) during several mood induction procedures. The mood induction focuses on four strong affective states and uses a variety of methods of induction. Early results are reported.

Keywords

Mood induction, Emotiv, training, mood

ACM Classification Keywords

H5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

General Terms

Design, Reliability

Introduction

Currently an issue in training is the ability for training to transition into effective task performance. As high testing scores do not necessarily correlate with on-task performance, one means of addressing this is mood-congruent memory [1]. By incorporating mood-congruence in the training tasks through intelligent tutors, improved memorization and recall might be achieved [2] and thereby improved training. Unfortunately, many current methods of mood assessment are invasive or difficult to set up, such as questionnaires, EEG caps and electrodes. As such, they interfere with learning processes and typical training procedures; negatively impacting the very training intended to be improved [8].

We have been investigating unobtrusive mood capture using multiple disparate sensing sources. Unobtrusive capture is preferable to obtrusive mood capture as it requires no effort by, and no interruption to, the trainee. Our target mood assessment system instruments the space around a desktop computer with commodity unobtrusive and multi-modal sensing technologies. Through mutual disambiguation using machine learning, the variances of each sensor are factored out with the strengths of one overcoming the weakness of the other. Several modalities have been explored with varying success including video, physiological sensors, a commercial EEG (Emotiv Epoc), and pressure-sensing chair and mouse instrumentation. While each unobtrusive measure itself is error-prone and variable, unifying the measures creates a robust assessor of mood.

Related Work

This project touches on multiple research topics. Its goals of responding to a trainee's affective state are similar in scope to affective computing [5] and intelligent tutoring systems such as AutoTutor [4].

Mood is only one aspect of an individual's affective state however. One hierarchical model of affect [9] organizes affect into three classes: emotion, mood and personality. Affective traits are predispositions to emotion and are enduring aspects of personality. Moods are transient but last longer than emotions which are brief and intense. Mood itself has been explained using two general scales of affective state. The first scale uses the three dimensions of pleasure-displeasure, degree of arousal and dominance-submissiveness [7] and is measurable by the pictorial Self-Assessment Manikin (SAM) [3]. The second scale uses two dimensions, the first being positive affect and the second being negative affect [10] and is measured with the PANAS-X (the expanded version of the Positive Affect Negative Affect Scale) questionnaire [11].

Several mood induction procedures (MIPs) exist [12]. Generally, negative moods are easier to invoke, compared to positive moods. Additionally, informing the participants about the experiment's purpose raises the MIPs' effect. Mood induction remains controversial and typically only a portion of the population can be induced [12]. A common issue is the influence of demand characteristics, i.e., how much are the participants reporting the mood because they believe they are expected to do so.

Creating a Mood Sensing Tool

A focus is to explore instrumentation of the desktop to unobtrusively obtain mood data and then develop an algorithm that mutually disambiguates among the data streams. The work is taken in steps: 1) create a mood induction procedure, 2) take direct and indirect measures, 3) filter out the non-induced participants using indirect measures, 4) find trends in the direct measures, with a preference for the unobtrusive, that reflect the mood changes found in the indirect data.

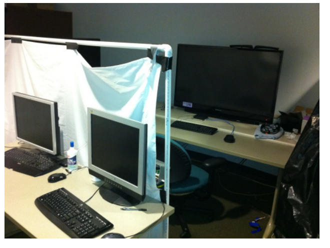
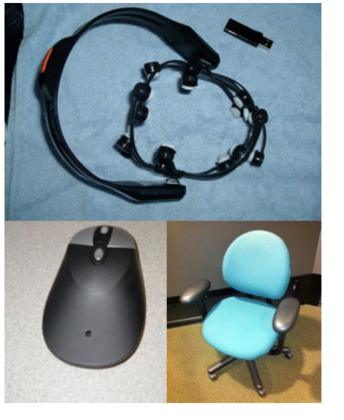


figure 1. The experiment setup was designed to reduce participant distractions and let the moderator, behind, observe and control the experiment.

An iterative approach was used to create our mood induction procedure. This involved piloting several approaches on roughly fifteen pilot participants. Westermann et. al [12] noted that the higher fidelity the MIP, the more that mood was induced. As well, larger display sizes convey greater attention and arousal [6]. Therefore, we presented a slideshow to participants while sitting directly in front of a large screen display. The slides were evocative images from the International Affective Picture System (IAPS) on which we placed mood-paired statements that participants were told to read to themselves. These statements were created by the authors, except for the neutral and happy statements obtained from the original Velten mood induction. The statements created by the authors were paired to the subject matter. Each slide was presented for 20 seconds and three neutral slides were followed by twenty-three mood slides. We created a slide deck for common stimulus conditions related to mood dimensions: happy (valence or pleasure), sexual arousal (arousal), and fright and disgust (dominance). Between stimulus presentations, participants were given the PANAS-X and the SAM. As well, in the beginning they were given the Big 5 Personality Test. Participants were elicited from emails sent to college Listservs, posted campus flyers, and military cadets. They were paid for their time and asked about preexisting emotional or mental health conditions. None of the subjects was excluded on this basis. Additionally, a fifth slide deck was created with happy and neutral images, shown after the experiment to reduce any vestigial induced mood.

Several sensing devices instrumented the environment and user (Figure 1). This included embedding a temperature/humidity sensor (SHT15) in a mouse and a chair with embedded pressure sensors (Figure 2), four on the bottom and four on the back (Tekscan FlexiForce).

figure 2. Several devices were used to elicit physiological data. We instrumented a mouse (left) with a heat/humidity sensor and a chair with pressure sensors (right). The Emotiv EPOC (top) was also used.



We also the used Thought Technology's skin conductance sensor (SA9309M) for Galvanic Skin Response and respiration sensor (SA9311M) to monitor breathing. Lastly, we used the Emotiv Technology's Epoc headset (Figure 2), which supports several measures of emotion: short term excitement, long term excitement, frustration, meditation and boredom.

Results and Future Work

To date, twenty participants have completed our final protocol. Early analysis has given some interesting insights. First, we agree with Velten that participants vary in their inducibility. We have found that the standard deviation in the PANAS-X scores is a good indicator of inducibility. Second, while still looking at the best way to interpret the Emotiv EEG data, it is interesting that changing slides creates clear changes in arousal. Third, conscientiousness in the personality test might be a good indicator itself of inducibility. Fourth, the chair data are difficult to use as the induction protocol results in participants not moving while staring at the screen. Lastly, the mouse returns useful data in that the arousal stimulus raises participant temperature and the frightened stimulus lowers humidity. Currently, we are conducting our analysis of the data. Future analyses will explore relationships between PANAS-X, SAM, Big Five Personality dimensions to the hierarchical emotions defined by the Emotiv Epoc software. This involves statistical and machine learning methods to create models of the participant's mood. We are also looking at tailoring models for better individual accuracy. Other methods of mood induction including video games (as higher fidelity may lead to more effective mood induction [12]) and the addition of boring and frustration stimuli will be explored.

Citations

[1] Blaney, P. (1986). Affect and memory: A review. Psychological Bulletin, 99, 229-246

[2] Bower, G. H., Gilligan, S.G., & Monteiro, K. P. (1981). Selective learning caused by affective states. J. of Experimental Psych.: General, 1981, 110, 451-473.

[3] Bradley, M., & Lang, P. (1994). Measuring Emotion: The Self-Assessment Manikin and the Semantic Differential. Journal of Behavioral Therapy and Experimental Psychiatry , 25 (1), 49-59.

[4] D'Mello, S., Picard R.W, and Graesser, A. "Towards An Affect-Sensitive AutoTutor," IEEE Int. Sys., SpIs. on Int. Educational Systems, 22(4), 2007, pp. 53-61.

[5] Picard, R. "Affective Computing", MIT Technical Report 321, 1995.

[6] Reeves, B., Lang, A., Kim, E., & Tatar, D. (1999). The Effects of Screen Size and Message Content on Attention and Arousal. Media Psychology, 1 (1), 49-67.

[7] Russell, J., & Mehrabian, A. (1977). Evidence for a Three-Factor Theory of Emotions. J. of Research in Personality , 11, 273-294.

[8] Sottilare, R. and Proctor, M. (accepted). Classifying student mood within intelligent tutoring systems (ITS). Journal of Educational Technology. .

[9] Tellegen, A., Watson, D., & Clark, L. (1999). On the Dimensional and Hierarchical Structure of Affect. Psychological Science, 10 (4), 297-303.

[10] Watson, D. (2000). Mood and Temperament. New York: Guilford Press.

[11] Watson, D. & Clark, L. Emotions, Moods, Traits and Temperaments: Conceptual Distinctions and Empirical Findings. In The Nature of Emotion (eds) Ekman, P. & Davidson, R. 1994.

[12] Westermann, R., Spies, K., Stahl, G., & Hesse, F. (1996). Relative effectiveness and validity of mood induction procedures: a meta-analysis. European Journal of Social Psychology , 26, 557-580.