Sensors Model Student Self Concept in the Classroom

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Abstract. In this paper we explore findings from three experiments that use minimally invasive sensors with a web based geometry tutor to create a user model. Minimally invasive sensor technology is mature enough to equip classrooms of up to 25 students with four sensors at the same time while using a computer based intelligent tutoring system. The sensors, which are on each student's chair, mouse, monitor, and wrist, provide data about posture, movement, grip tension, arousal, and facially expressed mental states. This data may provide adaptive feedback to an intelligent tutoring system based on an individual student's affective states. The experiments show that when sensor data supplements a user model based on tutor logs, the model reflects a larger percentage of the students' self-concept than a user model based on the tutor logs alone. The models are further expanded to classify four ranges of emotional self-concept including frustration, interest, confidence, and excitement with over 78% accuracy. The emotional predictions are a first step for intelligent tutor systems to create sensor based personalized feedback for each student in a classroom environment. Bringing sensors to our children's schools addresses real problems of students' relationship to mathematics as they are learning the subject.

1 Introduction

Traditionally, the User Model of an Intelligent Tutoring System (ITS) consists of registration information with or without statistics about interactions with the ITS [1, 2]. Registration information often includes age, gender, class standing, teacher, and other static information about learners. A limitation of this approach is that the only dynamic information that the ITS uses is based on the performance of the students. With the use of non-invasive sensors, we have the opportunity to enhance user models with sensor data that is a natural byproduct of the student's interaction with the ITS. Though the cost of such sensors has previously made them less accessible for classroom deployment, recent strides have been made to address this limitation. Arizona State University (ASU), in collaboration with the Affective Computing Group (ACG) at MIT, has developed 30 lower-cost versions of four sensors that have shown promise for their ability to detect elements of students' emotional expression. These sensors include a pressure sensitive mouse, a pressure sensitive chair, a skin conductance wristband, and a camera based facial expression recognition system that incorporates a computational framework that aims to infer a user's state of mind. At UMass Amherst, we have built on ASU's work by integrating the sensors and an Emotional Query intervention module with a traditional ITS user interaction based models to obtain the students' reported emotions as they interact with the tutor. This enables the User Model System (UMS) to compare sensor readings at the time of the emotional queries.

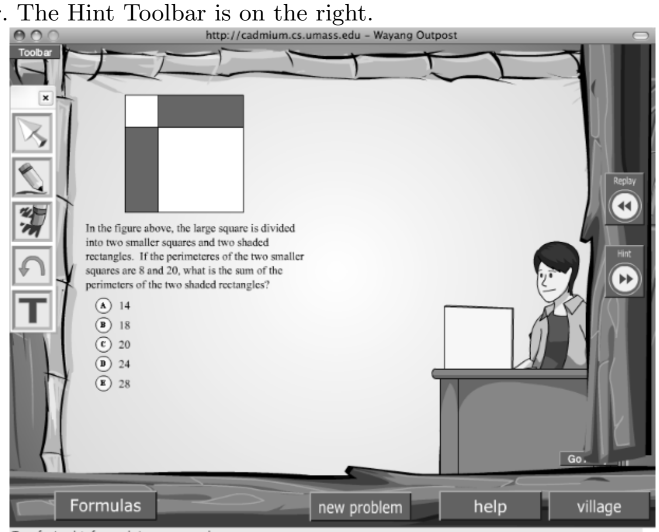
Ultimately we plan to have a UMS that models the student's interaction with an ITS in real-time and enables the ITS to intelligently tailor its behavior to a given student's needs. By personalizing the student's experience, the ITS can keep the student engaged and maintain or increase the student's interest and confidence in the subject. [3] is an example of having a character as part of the tutor giving non-verbal feedback, [4] is an example of a tutor that changes its feedback based on the tutor's emotional state in response to the student's emotion. For instance, a positive student emotional state elicits happiness in the tutor, which in turn rewards the student. In order to create the desired UMS, we have developed a platform comprised of three functional interacting components. These are (1) a sensor system for processing and integrating the sensor data described in Sec. 4, (2) a pedagogical engine for tutoring the student and collecting tutor data described in Sec. 2, and (3) a User Model system for integrating the sensor and tutor data to create a model of the student. We conducted three experiments using this framework in order to determine which sensor features have the best utility in terms of modeling students' perceived emotional state.

This paper describes our progress. Section 2 describes the Wayang Tutor and the student features that are used for the model. Section 3 describes related work. Section 4 describes the sensors that we use, their history, and the features for input to the User Model. Section 5 describes the integration of the sensor and tutor features. Section 6 describes the three studies performed to collect data for the user models. Finally, Section 7 discusses how the model can be used and ways to improve on the model we created.

2 The Tutor: Wayang Outpost

Our test-bed application for the experiments we describe in Sec. 6 was Wayang Outpost, a multimedia Intelligent Tutoring System (ITS) for geometry [5]. The tutoring software is adaptive in that it iterates through different topic sections (e.g. pythagorean theorem). Within each topic section, Wayang adjusts the difficulty of problems provided depending on past student performance. Students are presented with a problem and asked to choose the solution from a list of multiple choice options (typically four or five) as shown in Fig. 1.

Fig. 1. An example problem presented by the Wayang system. Jake is on the lower right corner. The Hint Toolbar is on the right.



As students solve problems, they may ask the tutor for one or several multimedia hints, consisting of text messages, audio and animations. The software includes gendered learning companions that are actual “companions” only: they don’t provide help; instead, they encourage students to use the help function; they have the capability of expressing emotions; and they emphasize the importance of effort and perseverance. Wayang has been used with thousands of students in the past and has demonstrated improved learning gains in state standard exams [5].

Wayang collects student interaction features in order to predict each student’s level of effort on the problems presented. These features, described in Table 1, are derived from the tutor data that is sent to the UMS. The majority of the tutor features could be extracted from other tutor systems with similar structure including a clear delineation of when attempts are made to answer the problem. Some features of Wayang are more specific, such as the number of hints or whether a particular gendered learning companion was used.

3 Related Work

There are a number of systems that already exist that either use similar sensors, detect similar affective states, or incorporate both tutor data and sensor data in order to model the student’s self reported emotion.

[6] uses a number of sensors to detect facial expressions, physiological features (heart rate, temperature, and skin conductance), and speech signals. The experiment uses 32 students simultaneously. Their application is to elicit emo-

Table 1. The nine tutor features below are selected along with the sensor features by using regression models to predict confidence, frustration, excitement, and interest. This table lists each tutor feature with an abbreviation and a definition.

Feature	Abbreviation	Definition
Solved On First	TsolF	Student's first attempt was correct.
Seconds to First Attempt	TsecF	Time in seconds to the first attempt.
Seconds to Solved	TsecS	Time in seconds to a correct attempt.
Number Incorrect	TNumInc	The number of incorrect responses.
Number of Hints	Thint	The number of hints the student selected.
Learning Companion (LC)	TLC	A value of 1 for LC and 0 for No LC
Group	TGroup	2 for Jake, 1 for Jane, 0 for Neither
Time In Session	TsesT	Time student has spent on interactive problems in the current session.
Time In Tutor	TtutT	Time student has spent on problems since the first use of the Tutor.

tional responses by the presentation of images rather than from using a tutor system. The emotions that they model are fear, anger, and frustration.

[7, 8] use a 3-D learning environment as their tutoring system. The systems monitor heart-rate and skin conductance in addition to the student-tutor interactions. [7] creates a model of frustration, while, [8] creates a model of self-efficacy, i.e. the student's belief in producing a correct answer.

Other work such as [4] does not use sensors at all, but only uses self reports to determine emotional state. They use three emotional ranges to model the student: boredom vs. curiosity, distress vs. enthusiasm, and anxiety vs. confidence. With the model of the student, they then create a model of their tutor to have emotional states that guide the tutor's responses. The focus of this system is the repair rather than the detection of emotional states.

Much of the past research has focused on small populations of students or lab studies, while our research uses large groups of students in real school settings. This is relevant because much research has shown that students lose interest and self-confidence in math over the course of the K-12 school system [9–11]. Bringing sensors to our children's schools addresses real problems of students' relationship to mathematics as they are learning the subject. This brings new tools to address their frustration, anxiety and disinterest/boredom while learning.

4 The Sensors

4.1 Sensor History

The sensors used in this study are similar to sensors that have been used in previous studies done by the Affective Computing Group (ACG) at MIT, but we have invested considerable effort on decreasing the overall production cost and improving the non-invasive nature of the sensors. Below we describe how our sensors compare to earlier sensors as well as some of the past uses of such sensors.

Skin Conductance Bracelet. The current system used in our research employs the next generation of HandWave electronics [12], providing greater reliability, lower power requirements through wireless RFID transmission, and a smaller form. This smaller form was redesigned to minimize the visual impact and increase the wearable aspects of previous versions. ASU integrated and tested these electronic components into a wearable package suitable for students in classrooms. Our version reports at 1Hz.

Pressure Sensitive Mouse. ACG developed the pressure sensitive mouse. It uses six pressure sensors embedded in the surface of the mouse to detect the tension in a user's grip and has been used to infer elements of a user's frustration level [13]. Our endeavors replicated ACG's pressure sensitive mouse through a production of 30 units. The new design of the mouse minimized the changes made to the physical appearances of the original mouse in order to maintain a visually non-invasive sensor, while maintaining functionality.

Pressure Sensitive Chair. The chair sensor system was developed at ASU using a series of six force sensitive resistors as pressure sensors dispersed strategically in the seat and back of a readily available seat cover cushion. It is a greatly simplified version of the Tek-Scan Pressure system (costing around $10,000) used in [14, 15]. This posture chair sensor was developed at ASU at an approximate cost of $500 per chair for a production volume of 30 chairs.

Mental State Camera. The studies in [14, 15] utilized IBM Research's Blue-Eyes camera hardware. This is special purpose hardware for facial feature detection. In our current research we are using a standard web-camera to obtain 30fps at 320x240 pixels. The camera is placed on the monitor of each student's computer. This is coupled with the MindReader library from [16] using a Java Native Interface (JNI) wrapper developed at UMass. The interface starts a version of the MindReader software, and can be queried at any time to acquire the most recent mental state values that have been computed by the library. In the version used in the experiments, only the six mental state features were available, but in future versions we will have the Facial Action Units available as well. These six mental features have a 65% to 89% accuracy with 5 out of the six features reported at above 76% accuracy.

4.2 Sensor Features

In order to create effective user models, we want to select the best feature set for our classification of the user's emotional self concept. Given that we don't have a huge number of examples, it is important to use as few features as possible while still receiving the value from each sensor. Thus the data from each sensor has been aggregated in the case of the Mouse and the Chair, and processed into five mental states, in the case of the Camera. We are using the raw Skin Conductance values for the Bracelet. The sensor features that are used for the studies are summarized in Table 2. These are used in conjunction with tutor features described in Sec. 2.

Table 2. The ten sensor features below are summarized by their mean, standard deviation, min and max values and then these 40 summarized features are selected by using regression models to predict confidence, frustration, excitement, and interest. This table defines the abbreviations for each feature.

Source	Feature	Mean	Std. Dev.	Min	Max
Camera	Agreeing	CmeanA	CdevA	CminA	CmaxA
Camera	Concentrating	CmeanC	CdevC	CminC	CmaxC
Camera	Thinking	CmeanT	CdevT	CminT	CmaxT
Camera	Interested	CmeanI	CdevI	CminI	CmaxI
Camera	Unsure	CmeanU	CdevU	CminU	CmaxU
Mouse	Pressure	MmeanP	MdevP	MminP	MmaxP
Seat	Sit Forward	SmeanF	SdevF	SminF	SmaxF
Seat	Net Seat Change	SmeanS	SdevS	SminS	SmaxS
Seat	Net Back Change	SmeanB	SdevB	SminB	SmaxB
Bracelet	Skin Conductance	BmeanC	BdevC	BminC	BmaxA

The classifiers in [14] used a similar sensor set in order to predict whether a user would click a button indicating frustration. They used the mean values computed over the previous 150 second window from when clicking the frustrated button. Fourteen sensor features were used to make four classifier systems using data from 24 students. Each system performed better than a classifier always picking no frustration, but no classifier was more than 80% accurate.

In addition to predicting frustration, our model is meant to predict excitement, interest, and confidence. The sensor features considered in our analysis are described below.

Mouse Feature. From the six pressure values from the mouse, each having the range $[0, 1023]$, we compute the following feature:

$$mousePressure = \frac{\begin{pmatrix} leftMouseFront + leftMouseRear + \\ middleMouseFront + middleMouseRear + \\ rightMouseFront + rightMouseRear \end{pmatrix}}{1023}, \quad (1)$$

which gives a potential range from $[0, 6]$, but empirically has the range of $[0, 2.5]$ in the High School (HS) study, and $[0, 1]$ in the two other studies.

Chair Features. We compute three features from the 6 chair sensors. The first two are based on the most useful features from [17]. These are the net change in pressure of the seat, and the net change in pressure of the back:

$$netSeatChange[t] = \begin{vmatrix} LeftSeat[t-1] - leftSeat[t] + \\ MiddleSeat[t-1] - middleSeat[t] + \\ RightSeat[t-1] - rightSeat[t] \end{vmatrix}, \quad (2)$$

$$netBackChange = \left| \begin{array}{c} lastLeftBack \;-\; leftBack \;+ \\ lastMiddleBack - middleBack + \\ lastRightBack \;-\; rightBack \end{array} \right| , \qquad (3)$$

The third chair feature is meant to determine if the student is sitting forward. From the three pressure values from the back of the chair, each having the range $[0, 1023]$, we compute the Sit Forward feature as follows:

$$sitForward = \begin{cases} 0 & \text{if } leftBack > 200 \text{ or} \\ & middleBack > 200 \text{ or} \\ & rightBack > 200 \\ 1 & \text{if } 200 >= leftBack > -1 \text{ and} \\ & 200 >= middleBack > -1 \text{ and} \\ & 200 >= rightBack > -1 \\ \text{NA} & \text{otherwise} \end{cases} , \qquad (4)$$

where NA is treated as no data.

Bracelet Feature. There are two values that we obtain from the wrist sensor, one is the battery voltage to inform us when the battery charge is low, and the other is the skin conductance in Microsiemens. Since there was no need to reduce the number of features, we processed basic statistics on the raw sensor values. In the future we plan to examine more sophisticated use of the skin conductance data such as the methods described in [8].

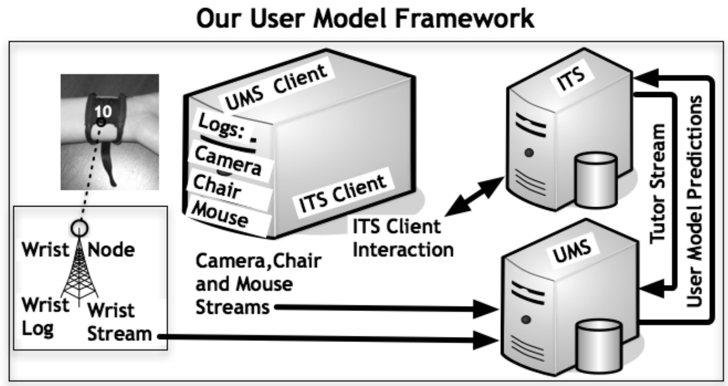
Mental State Camera Features. Of the six mental state features that the MindReader software identifies, we left out the disagree state, since agree and disagree are opposites. The five features we are left with are agreeing, concentrating, interested, thinking, and unsure. These mental states have a range from $[0, 1]$ as they are confidence values.

5 Feature Integration

In our framework, each feature source from each student is a separate stream of data. Hence we have five streams of data that each report asynchronously and at different rates. In order to merge all of the data sources, the wrist ID from each student, and a time of the report was needed from each source. An example of one client connected to our User Model Framework is shown in Fig. 2.

In our experiments, we used the logs rather than the sensor streams, since the streams are not yet informing a user model. In addition, the tutor does not yet create a stream of tutor data. Instead we used a database query to obtain the relevant tutor information, and fed it to the User Model System with the four sensor sources in order to time align the data and merge it with the correct student. The result is a database table with a row for every time stamp and

Fig. 2. A student at the client computer puts on a bracelet and starts the two client programs indicating the wrist ID of the bracelet. The bracelet sends Skin Conductance data to the Wrist Node, then logs bracelet data from all of the students in the classroom. The User Model System (UMS) receives the bracelet data through the Wrist Stream. The UMS client performs the same task as the Wrist Node for each of the other three sensor sources. The ITS logs student interactions, and sends Tutor Data to the UMS. The data is time synced based on the client's system time. The UMS uses all available streams of data to make user predictions to improve the ITS Client interaction.



wrist ID pair, and a column for each reported sensor value and tutor data value. Each cell in a row represents the latest report of the data source. If the data source has never reported or has not reported since the last tutor login or logout event with a corresponding wrist ID, then the value is -1 until the data source reports again. In this way the wrist IDs can be used by more than one student at separate time intervals, and the system will continue to work.

6 Experiments

We conducted three studies during Fall 2008 using our sensor system with Wayang Outpost. The HS study involved 35 students in a public high school in Massachusetts; the UMASS study involved 29 students in the University of Massachusetts; the AZ study involved 29 undergraduate students from Arizona State University. In the HS and UMASS studies, students used the software as part of their regular math class for 4-5 days, as it covered topics in the class. The AZ study was a lab study, where students would come to a lab in the university and use the software for one single session. Wayang worked the same way for all students, as introduced in Sec. 2, except for the fact that a student could be randomly assigned the female learning companion (Jane), the male learning companion (Jake) or no learning companion. In order to gather information on students' emotions, Wayang prompted students to report how they were feeling (e.g., *"how [interested/excited/confident/frustrated] do you feel right* *now?"*). Students answered this prompt by choosing one item from a five-point scale, where a three corresponded to a neutral value and the ends were labeled with extreme values (e.g., *" I feel anxious/ very confident"*). The queried emotion was randomly chosen, obtaining a report per student per emotion for most subjects. Wayang queried students on their emotions every five minutes, but did not interrupt students as they were solving a problem. During each student's interaction with Wayang, the four sensors described in Sec. 4 gathered data on his or her physiological responses.

6.1 Results

The three experiments yielded the results of 588 Emotional Queries from 80 students that include valid data from at least one sensor. The queries were separated into the four emotion variables as follows: 149 were about confidence/anxiety, 163 were about excitement/depression, 135 were about interest/boredom, and 141 were about frustration/no frustration. 16 of the student responses gave no answer to the Emotional Query. These results were used as examples for the Regression and the training and testing of the classification models.

In order to select a subset of the available features, a Stepwise Linear Regression was done with each of the emotions as the dependent variable, and tutor and sensor features as the independent variables. Since some students had missing sensor data, separate models were run pairing the Tutor Features with Sensor Features from one sensor at a time, and then finally with all of the Sensor Features. Results from the regression in Table 4 show that the best models for confidence, frustration, and excitement came from the subset of examples where all of the sensor data was available, and the best model for interest came from the subset of examples with mouse data available.

Table 3. Each cell corresponds to a linear model to predict emotion self-reports. Models were generated using Stepwise Regression, and variables entered into the model are shown in Table 4. The top row lists the feature sets that are available. The left column lists the emotional self-reports being predicted. R values correspond to the fit of the model (best fit models for each emotion are in bold). N values vary because some students are missing data for a sensor.

	Tutor only	Camera +Tutor	Seat + Tutor	Wrist + Tutor	Mouse + Tutor	All Sensors +Tutor	Best Sensor
Confident	$R = 0.44$ $N = 143$	$R = 0.61$ $N = 77$	$R = 0.48$ $N = 115$	$R = 0.40$ $N = 106$	$R = 0.48$ $N = 107$	$\mathbf{R = 0.63}$ $\mathbf{N = 68}$	**Camera**
Frustrated	$R = 0.55$ $N = 138$	$R = 0.60$ $N = 78$	$R = 0.61$ $N = 105$	$R = 0.55$ $N = 109$	$R = 0.59$ $N = 102$	$\mathbf{R = 0.62}$ $\mathbf{N = 67}$	**Camera**
Excited	$R = 0.39$ $N = 154$	$R = 0.40$ $N = 74$	$R = 0.45$ $N = 122$	$R = 0.39$ $N = 106$	$R = 0.45$ $N = 119$	$\mathbf{R = 0.56}$ $\mathbf{N = 64}$	**Seat+ Camera**
Interested	$R = 0.42$ $N = 133$	$R = 0.56$ $N = 75$	$R = 0.53$ $N = 107$	$R = 0.36$ $N = 101$	$\mathbf{R = 0.67}$ $\mathbf{N = 102}$	$R = 0.66$ $N = 62$	**Mouse**

Table 4 shows the features selected for each of the linear models. Looking at the best fitting models, highlighted in bold, it is interesting to see that at most two of the sensor sources and at most five of the available features are significant.

Table 4. This table lists the variables that the Stepwise Regression method selected as relevant, for each of the regression models in Table 3. Each of these features significantly contribute to the prediction of emotion self-reports ($p < 0.01$), and are listed in order of relevance (The feature at the top is the best predictor.) The abbreviations of these features are defined in Tables 1 and 2.

	Tutor context only	Camera + Tutor	Seat + Tutor	Wrist + Tutor	Mouse + Tutor	All Sensors + Tutor
Confident	TsolF Thint	TNumInc CminT CmaxC	TNumInc TsolF SdevF	TNumInc	TNumInc TsolF TsesT	**TNumInc** **CmaxC** **CmaxT**
Frustrated	TLC TNumInc Thint TsesT	TLC Thint TsesT CmaxI CminT	TLC TsesT TNumInc Thint	TLC Thint TsesT TNumInc	TLC TNumInc TsesT Thint TsecS	**CdevU** **TLC** **TsesT** **CminT** **Thint**
Excited	TGroup TNumInc	TNumInc CmeanI	TNumInc TGroup	TGroup TNumInc	TGroup TNumInc	**SmeanS** **CminI** **SmeanF**
Interested	TGroup	TGroup CminI Thint	TGroup	TGroup	**TGroup** **Thint** **MdevP** **MmaxP**	TGroup Thint CminI MmaxP

6.2 Cross Validation of the Linear Models

In order for the User Model system to give feedback to the ITS, the available sensor and tutor features can be put into a classifier and report when a user is likely to report a high value of a particular emotion. This likelihood could reduce and possibly eliminate the need for querying the user of their affective state. To test the efficacy of this idea, we made a classifier based on each linear model in the table. Rather than using the scale of one to five, the dependent variable of the classifier was 1 if the emotion level was high and -1 if the emotion level was not. Hence we used a classification threshold of 0 on the prediction.

For each model we performed leave-one-student-out cross validation. We recorded the number of True Positives, False Negatives, True Negatives, and False Positives at each test. Table 5 shows that the best classifier of each emotion in terms of Accuracy ranges from 78% to 87.5%. The best classification results are obtained by only training on examples that are not in the middle. This is likely the case because the middle values indicate indifference.

Table 5. This shows results of the best classifier of each emotional response. Accuracy of no classifier is a prediction that the emotional state is always not high. Values in parentheses include the middle values in the testing set as negative examples.

Classifier	True Pos.	False Pos.	True Neg.	False Neg.	Accuracy (%)	Accuracy (%) No Classifier
Confident All	28(28)	5(24)	10(16)	1(1)	86.36(63.77)	34.09(57.97)
Frustrated All	3(3)	0(0)	46(58)	7(7)	87.5(89.7)	82.14(85.29)
Excited Wrist	25(25)	9(37)	25(40)	5(5)	78.1(60.7)	53.12(71.96)
Interested Mouse	24(25)	4(19)	28(53)	7(7)	82.54(74.76)	50.79(69.90)

7 Discussion

We have presented a User Model framework to predict emotional self concept. The framework is the first of its kind – including models based on sensor data integrated with an ITS used in classrooms of up to 25 students. By using Stepwise Regression we have isolated key features for predicting user emotional responses to four categories of emotion. These results are supported by cross validation, and show improvement using a very basic classifier. The models from these classifiers can be used in future studies to predict a students' self-concept of emotional state on four ranges of emotion. These ranges are interest, frustration, confidence and excitement.

There are a number of places for improvement in our system. The first is that we used summary information of all of the sensor values. We may find better results by considering the time series of each of these sensors. In addition, the MindReader library can be trained for new mental states. This is one avenue of future work. Another place for improvement is to look at individual differences in the sensors. Creating a baseline for emotional detection before using the tutor system could help us to better interpret the sensor features.

Now that we have a basic User Model of students, the next step is to use this Model in the next experiments to send recommendations to the ITS. In order for this to be useful, the ITS needs to have some repair mechanisms based on the predictions from the User Model. Examples of this include encouragement, suggesting to the student to ask for a hint, and mirroring the emotion of the student.

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