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Computational Affect Detection for Education and Health

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COMPUTATIONAL AFFECT DETECTION FOR EDUCATION AND HEALTH

A Dissertation Presented

by

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COMPUTATIONAL AFFECT DETECTION FOR EDUCATION AND HEALTH

A Dissertation Presented

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To my beloved wife, Erin, and son, Isaac, who inspire me daily.

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ABSTRACT

COMPUTATIONAL AFFECT DETECTION FOR EDUCATION AND HEALTH

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Emotional intelligence has a prominent role in education, health care, and day to day interaction. With the increasing use of computer technology, computers are interacting with more and more individuals. This interaction provides an opportunity to increase knowledge about human emotion for human consumption, well-being, and improved computer adaptation. This thesis explores the efficacy of using up to four different sensors in three domains for computational affect detection. We first consider computer-based education, where a collection of four sensors is used to detect student emotions relevant to learning, such as frustration, confidence, excitement and interest while students use a computer geometry tutor. The best classier of each emotion in terms of accuracy ranges from 78% to 87.5%. We then use voice data collected in a clinical setting to differentiate both gender and culture of the speaker. We produce classifiers with accuracies between 84% and 94% for gender, and between 58% and

70% for American vs. Asian culture, and we find that classifiers for distinguishing between four cultures do not perform better than chance. Finally, we use video and audio in a health care education scenario to detect students' emotions during a clinical simulation evaluation. The video data provides classifiers with accuracies between 63% and 88% for the emotions of confident, anxious, frustrated, excited, and interested. We find the audio data to be too complex to single out the voice source of the student by automatic means. In total, this work is a step forward in the automatic computational detection of affect in realistic settings.

TABLE OF CONTENTS

Page

ACKNOWLEDGEMENTS . . . . **v**

ABSTRACT . . . . **vii**

LIST OF TABLES . . . . **xiii**

LIST OF FIGURES . . . . **xvi**

CHAPTER

1. INTRODUCTION **1**

1.1 Why Study Affect 2
1.2 The Study of Affect 4

1.2.1 Affective Channels and Labels 4

1.2.1.1 Faces 5
1.2.1.2 Voices 6
1.2.1.3 Physiology 8
1.2.1.4 Movement 8

1.2.2 Affect Classification 9
1.2.3 Target Applications 12

1.3 Contributions 12
1.4 Thesis Outline 13

2. BACKGROUND **15**

2.1 Affective Sensors 15

2.1.1 Education Use 15

2.1.1.1 Skin Conductance Bracelet 15

2.1.1.2 Pressure Sensitive Mouse 15
2.1.1.3 Pressure Sensitive Chair 16
2.1.1.4 Mental State Camera 16

2.1.2 Voice Sensors 17

2.1.2.1 Voice in Health 17
2.1.2.2 Voice in Emotion 17
2.1.2.3 Voice in Culture 18

2.1.3 Video Sensors 19

2.2 Classification as Prediction 20

2.2.1 Ideal Conditions 20
2.2.2 Deviations from the ideal 21

2.3 Classification Methods 21

3. USER MODEL FOR COMPUTER BASED EDUCATION 23

3.1 Related Work 24
3.2 Affect Detection System 25

3.2.1 The Tutor: Wayang Outpost 25
3.2.2 Sensor Features 27

3.2.2.1 Mouse Feature 28
3.2.2.2 Chair Features 29
3.2.2.3 Bracelet Feature 30
3.2.2.4 Mental State Camera Features 30

3.2.3 Feature Integration 30

3.3 Experimental Setup 32
3.4 Affect Classifiers 33

3.4.1 Cross-Validation of the Linear Models 35

3.5 Discussion 36

4. RANKING CLASSIFIERS FOR COMPUTER BASED EDUCATION 37

4.1 Introduction 37
4.2 Related Work 38
4.3 Data Collection: Sensors with Wayang Outpost in the Classroom 40

4.3.1 Setup 40
4.3.2 Tutor and Sensor Features 42

4.4 Method 42

4.4.1 Collection 44
4.4.2 Predictor Selection 44
4.4.3 Cross-Validation 44
4.4.4 Classifier Ranking 45
4.4.5 Validation with Follow-on Data 46

4.5 Results 46

4.5.1 Classifier Ranking 48
4.5.2 Validation with Follow-on Data 50

4.6 Discussion 50

5. SPEAKER DIFFERENCES AND HEALTH DIAGNOSIS 53

5.1 Related Work 53
5.2 Experimental Setup : Multicultural Study 55
5.3 Classification 56
5.4 Results 57
5.5 Discussion and Future Work 59

6. HEALTH CARE EDUCATION 61

6.1 Clinical Simulation 61
6.2 Experimental Setup 62
6.3 Video Features 63

6.3.1 Feature Extraction 64
6.3.2 Affect Classification 65
6.3.3 Pre-processing 66

6.3.3.1 Person Tracking 66
6.3.3.2 Tracking Algorithm 70
6.3.3.3 Tracking algorithm variants 73

6.3.4 Tracking Comparison 76
6.3.5 Tracking Results 76
6.3.6 Video Events 76

6.3.6.1 Feature Selection 79

6.4 Voice Features 81

6.4.1 Future work 82

6.5 Discussion & Future Work 82

7. DISCUSSION AND FUTURE WORK 84

7.1 Hypotheses Revisited 84
7.2 Lessons Learned and Future Directions 86

7.2.1 Computer Based Education 86

7.2.1.1 Sensors 86
7.2.1.2 Controls 87
7.2.1.3 Feedback 87

7.2.2 Speaker Differences and Health Diagnosis 87

7.2.2.1 Classifiers 87
7.2.2.2 Categories 88

7.2.3 Heath Care Education 88

7.2.3.1 Controls 88
7.2.3.2 Self-Reports 89
7.2.3.3 Other Judges 89

7.3 Summary 89

BIBLIOGRAPHY 91

LIST OF TABLES

Table | Page

3.1 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. 27

3.2 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. 28

3.3 Each cell corresponds to a linear model to predict emotion self-reports. Models were generated using stepwise linear least squares regression, and variables entered into the model are shown in Table 3.4. 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. 34

3.4 This table lists the variables that the stepwise regression method selected as relevant, for each of the regression models in Table 3.3. 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 3.1 and 3.2. 34

3.5 This table shows the results of the best classifier of each emotional response (confident, frustrated, excited, and interested). Accuracy of no classifier (last column) is a prediction that the emotional state is always low. Values in parentheses include the middle values in the testing set as negative examples. 35

4.1 The mapping of tags to text in Fig. 4.1 above. 41

4.2 Features used for each problem that includes an affective state label in order to train the emotion classifiers (features are shown in abbreviated form). The nine tutor features are shown on the left and the ten sensor features are on the right. Features used in a classifier that are significantly better than the baseline ($p < 0.05$) are in **bold**. 43

4.3 Summarization of the affect detection method. 47

4.4 These are the results of the feature selection. The baseline classifier for each emotion is just a linear model trained on a constant. The classifier names are the concatenation of an abbreviated emotion (e.g., confident, interested, and excited) and the contributing sensor features. If there are no sensor features, then Tutor comes after the emotion, and when there is more than one classifier with the same feature set a letter is added to disambiguate the names (e.g. TutorA is only tutor data, and TutorM is only tutor data, but the stepwise selection process had the mouse data available, but no mouse features were selected). Names in **bold** are for classifiers that performed significantly better than the baseline for that emotion in at least one way. 48

4.5 Classifier ranking using cross-validation data ($p < 0.05$). 49

4.6 This shows validation results of all classifiers that performed better than the baseline classifier during training. All values are the mean value per student. Fall specifies the training set based on the leave-one-student-out cross-validation, and Spring specifies the results of the classifiers trained on the training set (Fall 2008 Data), and tested on the validation set (Spring 2009 Data). Values in **bold** are significantly better ($p < 0.05$) than the baseline. 51

4.7 Classifier ranking using validation data from the Spring of 2009. All differences indicated by '>' are significant with $p < 0.01$. 51

5.1 The ten acoustical features below are selected by using a linear least squares stepwise regression models to predict gender, American vs. Asian culture, or one of four cultures. This table lists each feature with an abbreviation and a definition. 57

6.1 Cross-validated mean R^2 values for the five best trackers. Each cell corresponds to a linear model to predict emotion self-reports. Models were generated using a branch and bound linear regression. The top row lists the tracker. The left column lists the emotional self-reports being predicted and the group that reports are predicted for. R^2 values correspond to the fit of the model (best fit models for each emotion are in **bold**). Group A had one simulated patient and Group B had two simulated patients. Each group has 23 students reporting emotions. 79

6.2 The ten best classifiers, one for each emotion for each group. Trackers starting with an i are DF trackers using variant 4. f indicates using variant 3. g indicates using variant 5. a indicates the CAMSHIFT tracker, and b indicates using variant 1b. t indicates using variant 1a. s indicates using the faster variant of the DF tracker, and n indicates that just initialization is done. 80

LIST OF FIGURES

Figure **Page**

1.1 The Emotion Scale on the Left [50] and the Personal Interaction Coding Inventory on the right [15]. 11

3.1 An example problem presented by the Wayang system. Jake is on the lower right corner. The Hint Toolbar is on the right. 26

3.2 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. 31

4.1 An example of the Emotion query. Table 4.1 below has the values for each <> enclosed word, except for (<*Name*>), which is the name of the student. 41

5.1 The effect of pause length on extracting useful utterances for the classification of gender. The red line with boxes expresses utterances extracted with no buffer, and the blue line with diamonds expresses utterances extracted with a 100ms silence buffer on each side. 95% confidence intervals are shown. 58

5.2 The effect of pause length on extracting useful utterances for the two class classification of culture (American vs. Asian). The left shows the results for male subjects. The red line with boxes expresses male utterances extracted with no buffer, the blue line with diamonds expresses male utterances extracted with a 100ms silence buffer on each side. The right shows results for female subjects. The red line with down triangles expresses female utterances extracted with no buffer, the blue line with up triangles expresses female utterances extracted with a 100ms silence buffer on each side. 95% confidence intervals are shown. 59

6.1 Left: The key points for Group A with one simulated patient. The key points in this room were 1) The monitor, 2) the patient, and 3) the telephone. In this frame, the student is closest to the monitor, but actually interacting with the patient. Right: The key points for Group B with two simulated patients. The key points in this room were 1) patient 1, 2) patient 2, and 3) the telephone. In this frame the student is closest to patient 1. 65

6.2 Two examples of the Reading People Tracker. Yellow rectangles represent objects. Pink rectangles represent upper body. Red rectangles with a small inner rectangle represent heads. top: Multiple objects are found for one person, bottom: the foreground detection of the person begins to fade as the student stands very still. 67

6.3 Two examples of the CAMSHIFT tracker. The blue box is the center of the track, representing the head position. The red ellipse is the area being tracked. top: the tracker center stays near the student, but the size of the track is most of the frame, bottom: the tracker center goes to the wrong side of the patient. 68

6.4 An example of the Lucas-Kanade tracker. The head region is selected by hand. As the student moves around the ‘good features to track’ (in green) disperse away from the head. 69

6.5 Two examples of the distribution field tracker. Blue box represents the area being tracked, in this case, the head of the student. top: tracker incorrectly selects filing cabinet, bottom: tracker incorrectly selects a box with dials 70

6.6 Left: Top ten trackers in order of increasing mean squared error. Right: Box plot of distances from ground truth for top ten trackers. Trackers beginning with ‘n’ use only initialization, trackers beginning with ‘a’ are variants of the CAMSHIFT tracker, and trackers beginning with ‘i’ are the DF trackers. 77

6.7 The predicted head positions of one student for two different trackers. Blue points predict closest to monitor. Green points predict closest to patient, and Orange points predict student closest to the telephone. Left: heuristic detection (no tracking). Right: distribution field tracker 78

6.8 The PICI features that are common between groups A and B. 80

CHAPTER 1
INTRODUCTION

One of the strongest links between the way computers work and the way people think was defined by the field of cognitive psychology [3], specifically the information processing approach to cognitive psychology. The information processing approach considers that the essence of the mind is processing the information available to people in their environment. While computers use ones and zeros to process, people have visual, audio, touch, smell, taste, and balance stimuli. In addition, these stimuli from the environment are translated from physical signals to electrical signals and then processed by the brain. According the information processing approach of cognitive psychology, the mind takes in this sensory information, processes it based on a set of rules, and comes up with answers, or decisions. In essence, this information processing approach uses a computer paradigm to describe human cognition. Many great advances in psychology came from this approach, including a learning mechanism for computation called the neural network [80, 104]. Information processing is not traditionally concerned with emotion; however, Herb Simon expressed that emotion plays an important role in cognition, and that information processing theories should include an "intimate association of cognitive processes with emotions and feelings" [117]. This proclamation was made in 1967 as a response to Neisser's article with the headline "The view that machines will think as man does reveals misunderstanding of the nature of human thought" [89]. However, only recently have researchers seriously considered including emotion as an integral part of the architecture [12, 13, 28, 60].

The use of sensors to detect emotion has been attempted with varying levels of success for many years.

In this chapter I discuss why the study of affect is important for the field of computer science, and how affect is currently studied in general, and in the case of humans interacting with computational systems.

1.1 Why Study Affect

Emotional intelligence is a clear factor in education [37, 73, 74], health care [90], and day to day interaction [49]. In education, Wigfield and Karpathian found that low motivation indicates less learning [132]. For health, there is evidence that a positive emotional state can speed up recovery [90]. In addition, the onset, progression and improvement of health and disease processes have been noted to impact the human voice and produce unique changes in acoustic signals [124]. For personal interaction there is evidence that individuals self-modulate their mood in anticipation of interacting with another person [49]. In addition, nurses do 'emotion work,' modulating their expression, to better care for patients [84]. But this evidence alone, may not be enough to warrant studying affect for the purposes of computation.

Computer use in educational settings has been increasing rapidly since 1993 [119]. In 2003, 83.5% of students age 3 and above used computers in school up from 59% in 1993. In addition 47.2% of students age 3 and above in 2003 used computers at home to do school work up from 14.8% in 1993. With this increase in use of computers for educational purposes, and the link between understanding affect of students and their performance, there is a clear need for computers to begin to understand the emotions of students.

The study of affect for health purposes has been a research area for many years. However, more recently there has been more of a push toward quantitative measures of emotion, and these quantitative measures are an obvious place for computational tools to assist in health diagnosis and care. Several disorders involve emotional well-being or emotional understanding (or lack thereof) as a major part of the disorder. These include schizophrenia, autism spectrum disorder (ASD), and major depression. In addition, a number of physical disorders present with similar symptoms of vocal production as some of these affective disorders. These include childhood apraxia of speech (CAS) and parkinson's disease. Typical work involving quantitative measures of affective signals in these conditions involves a large amount of human labor to segment, label, and analyze the audio data. Computational methods are desired to free the practitioners from the labor involved in identifying the quantitative measures, and instead focus on the diagnostic tasks of differentiating healthy patients from those with a condition, and, from those, determining what condition the patient has.

From a broader point of view, a computational understanding of emotion can improve our day to day interactions. If your computer could respond to your mood, then it could potentially present more mood relevant material to you. In addition, it may be able to remedy a bad mood by producing mood–appropriate music or other media. As more houses are instrumented with video and audio sensors, a computerized house with affective awareness could be aware of one or more occupants' emotional state, and act appropriately. One such scenario would be for an elderly person who wants to live at home, but needs extra support. The computerized home could potentially observe interactions of the elderly person with other people, and keep track of who had positive effects on the person. Then, if later, the elderly person were in a bad mood, one of the people with good interactions could be invited over by the computerized home. In addition, if the elderly person had a visitor who was a stranger, someone could be notified if the elderly person was affected in a negative way by the visit. Since human mood and affect in general are an integral part of life, and computers are becoming more and more integral into human life, computers should detect affect in order to improve human computer interactions.

1.2 The Study of Affect

In order to make the study of affect useful for computers, we need a quantitative description of affect. The use of electronic sensors for affect detection allows for quantitative measure, however there is not yet agreement within the research community on the best way, or the “gold standard,” for validating these quantitative measures. Even without a “gold standard,” the method for quantitative measure is similar to that of the scientific method of physical phenomena. The main difference is that repeatability is more difficult due to inability to have purely controlled experiments, and due to the fact that the nature of the object of experiment, namely the human, is often changed by the experience of the experiment. This leads to empirical results that can yield significant statistical results but do not give too much insight on an individual event involving an individual person. This section will discuss 1) the affective channels that are available and methods for labeling them, 2) how computational classification of affect can be performed given these channels and labels, and 3) the target applications for the current body of work.

1.2.1 Affective Channels and Labels

People express emotions in many ways. Wilhelm Wundt described gesture communication as originating from “emotion and the involuntary expressive movements that accompany emotion” [135]. Wundt elaborated that actions in the face and the body can be used to determine emotion, and that gestural communication with emotion is able to elicit a similar emotion in the recipient of the communication. The knowledge that humans involuntarily display their emotion, and that this display can be observed and detected, is the basis for studying affect through observation and sensors. Contemporary work utilizes four different channels for affect, namely faces, voices, physiology and movement. Wang et al., [130] have used computational facial expression analysis for understanding emotion impairments in schizophrenia. Busso et al., [20] use features of fundamental frequency in voice to determine basic emotions in speech. Mandryk and Atkins [77] used physiological data such as Galvanic Skin Response (GSR), cardiovascular, and electro-myogram (EMG) data to detect emotion of people playing a video game. Camurri et al., [23] created a gesture analysis tool for looking at emotional expression in music and performance called EyesWeb.

The next few paragraphs discuss more detail of how faces, voices, physiology, and movement have been used to study affect. Each channel has a variety of features to choose from, and a variety of methods to label and categorize emotion. Several research issues remain to be answered. What defines the ground truth emotion? Is self-report accurate? Are quantitative metrics accurate and sensitive to note differences in humans with respect to affect, cultural, and linguistic differences? Is consistency of labeling indicative of quality? How important is the context of the experience in determining the emotional state of the participant? Each of these questions are addressed differently by each work discussed below. Hopefully some clarity will be gained by looking at these different approaches.

1.2.1.1 Faces

One early set of studies of facial expression involves the elicitation of various facial expressions through electrophysiological stimulation of facial muscles by Guillaume-Benjamin Duchenne [42, 43]. Duchenne found that some muscles have a complete control over particular expressions, while other muscles have partial control over the same expressions. Duchenne performed experiments by external manipulation, while the computer allows modern researchers to do observational experiments, in which the computer collects quantitative measurements of how facial expressions are made during a particular affective state or activity. Charles Darwin drew analogies between animal and human expression as a continuing argument that man evolved from a “lower animal form” [36]. In his work he dedicates eight chapters to “special expressions of man." These include suffering and weeping, anxiety and despair, joy and love, reflection and ill-temper (frowning), hatred and anger, contempt and disgust, surprise and fear, and finally shame and modesty.

From this set of emotions, Paul Ekman empirically determined which of these emotions were universally observed [44, 45]. That is, which of these emotions would be recognized when viewing a still image of a person expressing the target emotion. From this, Ekman found six universal emotions anger, joy, fear, disgust, surprise, and sadness [44, 45]. In addition, this work brought about the facial action coding system (FACS), which specifies particular visually observable motions in the face that make up emotional expression. The FACS is the basis for much of the computational detection of emotional expression in faces [33, 137].

In our intelligent tutoring system, we use a facial feature tracker that uses FACS-like features to detect interpersonal mental states such as agreeing, disagreeing, unsure, thinking, concentrating, and interested [47].

1.2.1.2 Voices

Computational voice processing started in 1928 with Dudley's vocoder (VOice CODER) [111], which digitizes and synthesizes voice. The vocoder was designed as a method for efficient electronic transmission of speech for Bell Telephone Laboratories. Some uses of vocoders are for the encryption of voice, for blind people to listen to recorded books at a fast rate, and to help partially deaf people hear speech better. The technology for the vocoder evolved into many signal analysis tools specific to voice processing. The sound spectrograph [68] was the first device for producing visual printouts of speech called spectrograms. Before this, oscillographs were used for detecting patterns in speech related to emotion [118]. Voice analysis is concerned with vocal differences and quality.

The first earnest attempt to conduct a quantitative study to test for emotional content in the voice was in 1935 [118]. In this study, participants produced the prolonged 'ah' sound multiple times after listening to a happy or sad musical piece, and after reading a happy or sad literary piece. Nineteen participants (9 male and 10 female) were recorded by an oscillograph attached to a condenser microphone that was a fixed 27.5 cm distance from the teeth. In addition the participants were recorded by a psychogalvonometer, which was the de facto emotion detector. Participants were also asked to self-report their emotional state. In all cases, the psychogalvonometer indicated emotional responses from the stimuli, and for many of the participants, there was a difference in the intensity and pitch of the happy vs. sad 'ah's.

In 1985, Robert Frick completed a survey of studies that explored the classification of emotion using prosodic (non-verbal) features in speech [55]. His survey discusses a number of features in the audio signal correlated to emotions. One finding of note is that arousal was thought to be indicated by the pitch height, range, loudness and rate of speech. In 1993, Murray and Arnott reviewed emotion literature and identified a set of features for five 'basic' emotions [87]. In 1995, Titze et al., enumerated a set of standards in order to control for reliability and validity of the acoustic measurement and voice outcomes while performing and analyzing voice recordings [124]. These standards were adopted for the Consensus Auditory-Perceptual Evaluation of Voice (CAPE-V) [140], and they allow for a clearer signal, but they may not be feasible in all settings where audio analysis is to take place.

More recently work has been done to determine whether there emotions that are universally recognized from voice [48, 108]. In addition successful classifiers have been made for acted voice using only the features, including voice changes, related to pitch, a.k.a. fundamental frequency (F_0) [20].

1.2.1.3 Physiology

Physiology is primarily studied for the purposes of health care. However, physiological signals have been used for research in emotion since the early twentieth century. The first device used was the psycho-galvanometer, which measures skin conductivity [131]. It was used to derive associations of affective tone from hearing different words. Other signals arising from physiology include respiration, heart rate, motor response in the face, and electrical activity in the brain. In general, physiological signals are obtained by attaching a sensor to the human body, and in the past this has meant that the person attached to these sensors was tethered by a wire of some sort. Recently, wireless sensors have been created for many physiological sensors, making them usable in more natural settings. However, little work has been done to realize this possibility, and the majority of experiments of emotion using physiological sensors are still performed in a lab-controlled environment.

1.2.1.4 Movement

Though Darwin suggested specific movement patterns to particular emotion, as discussed by Wallbott [128], he was not specifically interested in the detection of such emotions. In 1998, Wallbott performed experiments with multiple judges coding human movement of actors expressing different emotions to a video camera. These included upper body, shoulder, head, arm, and hand motions. In addition three quality measures were taken 1) movement activity, 2) expansiveness/spatial extension, and 3) Movement dynamics/energy/power. there was between 73% to 99% agreement between two coders with 224 recordings. Each recording was 2 to 3 seconds, and the actor's face was masked during the coding process. A similar approach was created by Bianchi-Berthouze in 2003 for computational recognition of affect in gesture [14]. In this study, a motion capture system was used to convert gestural information from the video using markers on the body, to an avatar representing the gestural information.

The frame of the avatar with the moment of extreme expression of the emotion was hand selected and labeled by a majority vote of 114 judges. These hand selected, frontal view frames were used in a neural network called CALM to categorize the avatar gestures as emotions. The CALM system got an average of 94% accuracy on the training set, and was able to keep it's accuracy above 70% with up to 5% random noise added to the training data as a test set.

In 1999, Camurri et al., began the creation of a system for the computational analysis of emotion in dance performances [22]. They used Rudolph Laban's "Effort Theory" to attempt to computationally capture four features of effort in dance: space, time, weight, and flow. This resulted in a video based system called EyesWeb [23], which extracts the silhouette of a person and measures a set of effort based features that can be related to the emotion of the dancer. Further work was done by Castellano et al., using the EyesWeb system where acted emotion was detected on the valence-arousal axes based on front facing actors and their arm movements [25]. The EyesWeb tool is designed to be interactive with a human user, and so it could not be used for the purposes of the studies in this work.

Detecting emotion of a person interacting with the environment while not specifically facing the single camera in the room is a novel contribution. The work presented here is a first step towards this goal, and there is a large potential for refinement by using some of the more specific features found by the above mentioned research.

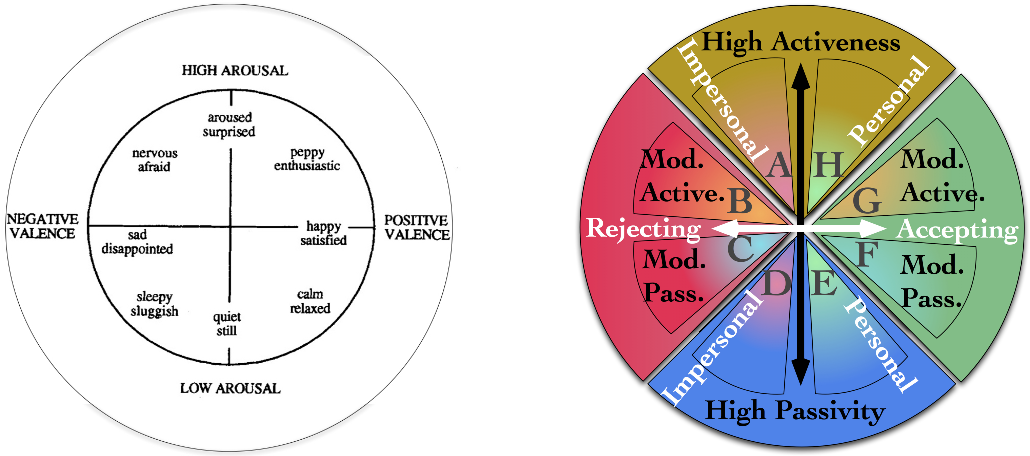
1.2.2 Affect Classification

Researchers have categorized the observation of emotion in a number of ways. The two most prevalent are 1) a two-dimensional feature space, and 2) a discrete set of classes for emotion.

Many words can be used to describe a person's emotion; however, there is a need to limit the number of emotional dimensions used for computation. This can be done by either picking the top n emotions, where $n < 10$ or it can be done by mapping the labels to a lower dimensional scale. This scale is usually a two-dimensional scale, but sometimes three dimensions are used. One of these two-dimensional feature space consists of valence (or the pleasantness of an experience) ranging from negative to positive, and the other is arousal ranging from low to high [50]. This two-dimensional space tends to be adequate for generating agreement when placing an affective label on it and has been used in connection with observing facial expressions and physiological features since 1954 [106, 110]. This two-dimensional scale of valence and arousal is shown in Figure 1.1(a).

A similar two-dimensional scale developed by Ralph Bierman was created for the purpose of personal interaction [15]. This is called the Personal Interaction Coding Inventory (PICI). The two-dimensions are rejecting-accepting and passive-active. They relate to how one individual interacts with another. This scale is shown next to the valence and arousal scale for comparison in Figure 1.1(b). Though we do not use the valence and arousal dimensions directly, they may become useful factors for audio. In addition the PICI may be a good first step for looking at personal interaction. In the case of a student interacting with an intelligent tutoring system, this scale may be useful at the extremes of accepting and rejecting, however the personal and impersonal parts of the scale may be skipped altogether.

When picking a subset of emotional labels, there are a number of ways to do it. A common method is to select labels relevant to a condition. For instance, emotions are chosen that are universal in some way, such as in visual or audio perception, or are important in a particular domain, such as education. Paul Ekman found that six of the ‘basic’ emotions are cross-culturally universal [45] when observers are asked to label pictures expressing these emotions. These emotions are anger, disgust, fear, joy, sadness, and surprise. In 1978, Ekman developed a more direct approach for determining emotion in facial expressions. This approach is based on the muscles



(a) Feldman's valence and arousal dimensions of emotion [50].

(b) An illustration of Bierman's personal interaction coding inventory (PICI) [15].

Figure 1.1. The Emotion Scale on the Left [50] and the Personal Interaction Coding Inventory on the right [15].

in the face that are activated when certain emotions are evoked in a human. These are called facial action units (AUs), and the system is called the facial action coding system (FACS) [44]. A review of studies by Zeng, et al., discusses many studies to detect emotion classes or AUs with computers using both acted and spontaneous facial expression in still images and video [137]. The emotion classes and AUs that are detected differ depending on the study, and the data sets used for training and testing are often different, so it is difficult to compare the results. Of note, as many as 32 AUs have been classified by computational methods at 86% accuracy using individual still images with a rule based system [92]. Though most of the studies look at basic emotions, there are a few that detect non-basic affective states from deliberately displayed facial expressions. Two studies explore the detection of fatigue [57, 65]. One study explores the detection of levels of interest after detecting basic emotions [136]. Other studies detect mental states such as agreeing, concentrating, disagreeing, interested, thinking, and confused [46, 47, 66], and this is the video system that is used in the current research for video emotion detection.

In addition to facial expressions, work has been done to find cross-culturally universal emotions detectable by listening to voices [108]. Scherer found five emotional states detectable in the voice. These are anger, fear, joy, neutral, and sadness.

A number of emotional labels are used in computer based education, including frustration, fear/anxiety, shame/embarrassment, enthusiasm/excitement and pride [91]; joy, distress, admiration, and reproach [30]; boredom, confusion, flow, frustration, and neutral [40]; and confident, excited, frustrated, and interested [8]. One goal of these features is to label points where a computer tutoring system can modify its interaction with the user. The interaction can change by modifying the task, offering emotional support, offering cognitive support, or changing the presentation of the task.

1.2.3 Target Applications

We explore three target applications of affect detection 1) computer based education, 2) speaker differences on the basis of gender, culture/race and health diagnosis, and 3) health care education. Specifically we use multiple sensors to explore the efficacy of detecting the affective state of students using an intelligent tutoring system (ITS) in a classroom environment. We extract affective features of audio recordings of clinical interviews in order to automatically classify gender and culture of patients. We extract movement features from video recordings of nurses in training while taking a practical examination in order to classify their emotions from the test.

1.3 Contributions

There are five contributions in this dissertation.

1. We show that affective learning states can be computationally determined in both computer-based and health care education.

2. We show empirical evidence that the affective features of voice are useful for the computational classification of gender, culture, and race.

3. We propose a novel method to track the head of a single person. This method illuminates key problems that need to be solved in computer vision for the long term real-time tracking of people.

4. We create a novel method to use video data to successfully classify self-reported emotions in clinical simulation evaluation environments.

5. We show two examples of the successful use of sensors for research outside of the laboratory.

1.4 Thesis Outline

This dissertation is organized as follows. This chapter introduced the problem of detecting emotion for education and health care and described the scope of this work. Chapter 2 gives a background to the sensors used for affect detection, and the methods of classification for the prediction of affect. Chapter 3 discusses the use of affective sensors in a classroom environment with Wayang Outpost, an intelligent tutoring system (ITS) that teaches mathematics. The following hypotheses are explored: 1) Sensors can effectively augment tutor logs in order to predict the self-reported emotions of students. 2) Linear least squares classifiers built from the tutor and sensor data can predict high vs. low levels of frustration, confidence, interest, and excitement. Chapter 4 continues the computer based education study by exploring how well the classifiers trained in Chapter 3 work with a separate larger population. One hypothesis is explored from different perspectives: The accuracy, specificity, and/or sensitivity of the frustration, confidence, interest, and excitement classifiers that use tutor and/or sensor features will continue to perform significantly better than the baseline classifier for the given emotion on a novel population. Chapter 5 introduces the challenges of health diagnosis as well as identifying speaker differences using voice features related to the emotional expression of speech. We explore data set of healthy participants from different cultures and races to extract affective voice features for the purpose of classifying gender, culture, and race. This chapter addresses the hypothesis that the method of feature selection and linear least squares classification will transfer to the voice domain. Chapter 6 discusses a novel application for computational affect detection and classification. The goal of the system is to accurately detect the self-reported emotion of a student nurse from the video and audio recordings of a practical clinical simulation evaluation in order to help the instructor identify students who are likely to leave the program without intervention. The hypotheses of this chapter are: 1) Low confidence is correlated with high anxiety in learning situations. 2) Available methods for real-time people tracking are adequate for tracking the nurses in the video. 3) PICI related features in the video will help to predict or classify the self-reported emotional state of the student. 4) Contemporary methods for automatic extraction of audio will be sufficient to separate the student nurses voice from other sounds and voices in the audio recording. 5) Prosodic features will be relevant for emotional change. Chapter 7 concludes with a discussion of the results and limitations of this research in addition to future directions for research in computational affect detection for education and health.

CHAPTER 2

BACKGROUND

2.1 Affective Sensors

2.1.1 Education Use

The four sensors used in the current Computer Based Education study are similar to sensors that have been used in previous studies done by the Affective Computing Group (ACG) at MIT. However, Arizona State University (ASU) invested considerable effort to decrease the overall production cost and improve the non-invasive nature of the sensors. We compare the ASU sensors to their predecessors as well as some of the past uses of such sensors.

2.1.1.1 Skin Conductance Bracelet

The current research employs the next generation of HandWave electronics [121], 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. This version reports at 1Hz. The bracelet sensor prototype parts came at a discounted price of $150, with 3 hours of assembly time, and the radio to communicate with the sensors for the classroom costs $200.

2.1.1.2 Pressure Sensitive Mouse

ACG developed the pressure sensitive mouse [97]. It uses six pressure sensors embedded in the surface of the mouse to detect the tension in a user's grip and it has been used to infer elements of a user's frustration level. Our endeavors replicated ACG's pressure sensitive mouse and produced 30 units to be used in a classroom. 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. The parts for the mouse cost $200 plus 3 hours of assembly.

2.1.1.3 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 research by ACG [19, 66]. This posture chair sensor was developed at ASU at an approximate material cost of $200 plus 2 hours of labor for assembly and testing per chair for a production volume of 30 chairs.

2.1.1.4 Mental State Camera

The studies by ACG [19, 66] utilized IBM Research's Blue-Eyes camera hardware. This is special purpose hardware for facial feature detection. In our current research we use a standard $50 web-camera to obtain 30 fps at 320x240 pixels. The camera is placed on the monitor of each student's computer. This is coupled with the MindReader library from el Kaliouby [47] 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 current experiments, we use the six mental state features (agreeing, disagreeing, concentrating, interested, thinking, and unsure), but not the facial feature point or action unit detections. The six mental features have a 65% to 89% accuracy with five out of the six features reported at above 76% accuracy when compared to the ground truth acted expression data

[47]. The MindReader software is under license from MIT, and it uses a facial feature tracker licensed by Google.

2.1.2 Voice Sensors

2.1.2.1 Voice in Health

During a clinical psychological interview, many different rating systems are used to classify affective disorders. For example, to identify schizophrenia, clinicians use instruments such as the Scale for the Assessment of Negative Symptoms (SANS) [4]. Many of the symptoms the clinician must identify have to do with how the person speaks, including affective flattening, blunted affect, the inability to experience or express a normal range of affective responses, emotional dullness, pervasive apathy, poverty of speech and psycho-motor retardation [120]. Since these symptoms are indicative of schizophrenia and can be detected by our ears, some researchers have found the corresponding speech signals that can be processed by a computer [4, 120].

Diagnosing depressed patients has a similar set of rating instruments. For example, reduced speech flow and prosody are both indicative of depression during free speech tasks, though not as much during reading tasks. In addition, acoustic features are more discriminating depending on whether the depressed person is categorized as having psycho-motor agitation or psycho-motor retardation [2]. A computer system has been created to semi-automatically distinguish between a highly depressive tendency and a mildly depressive tendency [123]. The features utilized only included pitch, amplitude range and utterance speed.

2.1.2.2 Voice in Emotion

Busso et al., recently found that the fundamental frequency and it's derivative can each be broken down into fourteen statistics, eleven of which can be used for sentence level processing, and eleven of which can be used as a voiced level statistic. These features can be used in a logistic regression classifier to predict levels of different emotions such as anger, happiness and sadness using 3 different emotional databases. Accuracies between 73% and 98% were attained where the baselines were between 54% and 89%. There was no ranking to see if the classifier was significantly better than the baseline, however a large number of the emotion classifiers have R^2 values above 0.63.

2.1.2.3 Voice in Culture

Walton and Orlikoff tested the ability of people to recognize differences between race solely on voice was tested in the distinguishing between white and black American voices [129]. Twelve judges, six experienced speech pathologists and six inexperienced speech pathology students were able to detect race with 60% accuracy. Since the mean pitch, first and second formant frequencies were not distinguishable between groups, the authors concluded that people must use spectral information and not pitch information to distinguish between race. Ryalls et al., found that voice onset times (VOT) for specific vowels and consonants were significantly different between Caucasian and African American subjects [107]. They also found significant differences of VOT for gender.

Andrianopoulos et al., [5, 6] identified significant differences between healthy speakers on the basis age, gender, culture and race by teasing-out subtle and salient features of the acoustic signal that differentiated four different cultural and racial groups of speakers. As predicted, male speakers voices regardless of culture and race were significantly lower in pitch compared to their female counterparts. Moreover, Mandarin Chinese and Hindi Indian males and females prolonged the three universal vowels, [a], [i] and [u], with significantly higher pitch voices compared to their Caucasian and African American male and female counterparts. Males regardless of culture and race exhibited significantly greater frequency and amplitude perturbation compared to their female counterparts. More recently, the subtle and salient differences in speakers with neurodevelopmental programs, such as an Autism Spectrum Disorder (ASD), are being studies by these researchers. To date, these authors have found similar trends in those individuals with ASD in that they speak with significantly higher pitch voices, with fewer semitones and restricted pitch ranges. These acoustic features noted in these populations support that individuals with ASD speak with higher pitch voices with 'monopitch' and 'monoloudness' [127].

2.1.3 Video Sensors

The majority of research studies of affect detection using video utilizes facial expressions. A survey of affect recognition by Zeng, et al., discusses the state of the art in this area and most of the work involves facial expression as its primary source of affect [137]. The affect that is detected is mostly either the Facial Action Units [44] based on musculature, or the six basic emotions of happiness, sadness, fear, anger, disgust, and surprise, which were found to be detected universally across cultures by Ekman [44, 45].

Facial expressions and extracted facial features can be used without a problem with video processing for intelligent tutors. However, for the purpose of investigating features of personal interaction, the detected features will need to be used in a different way. Similarly, for the case of observing two people interacting in a room when they can move freely around the room, the facial view of the person may not be available. In addition, when looking at one person's impact on another person, features such as proximity, gaze, and body language may be more important. Looking at full body motion in video has been done for identification [96] and for estimating interaction cues such as head pose, fidgeting, body pose, pointing, and hand raising [27].

2.2 Classification as Prediction

One goal of this dissertation is to use classification in order to predict the affective state of a person. Prediction is possible since people express their emotions in ways that are detectable by sensors. Simply put, a classifier takes as input a finite number of features, and based on the value of these features decides into which category the input fits. In the case of predicting emotion, this translates to taking sensor features and deciding which emotion the person is displaying.

However, using classification as a method for prediction has a number of risks. 1. Classifiers generally do not learn on the fly. 2. Individuals exhibit the same emotion in many different ways. 3. The affective signal may become contaminated due to ambient noise and other environmental factors. 4. Cues for emotion overlap with cues for other expression such as communication and language.

2.2.1 Ideal Conditions

To date, the ideal conditions for classification are:

1. Large population size.
2. Large set of data.
3. Data sample evenly distributed over the population in question.
4. Balanced sample from classes.
5. Independent features.
6. Data drawn from independent and identically distributed (i.i.d.) or exchangeable random variables
7. Implementation of control variables to increase reliability and validity of classifications systems given the current state of the art in technology.

2.2.2 Deviations from the ideal

In the case of emotion classification, as in many other types of classification, the ideal conditions described above often don't hold. Population size can be as small as one person, in which case the goal is to have a method for personalization in a short period of time, and often studies involve fewer than 50 participants. Due to availability of the participants and the sensors, the number of samples per participant is usually pretty low. The population sample is often very skewed due to most experiments being done in universities with university students [61]. For emotions, a balanced sample from each category is easy to record if the emotions are acted, less so if elicited, and difficult if the emotions occur naturally. It is unlikely that the features are independent, since all of the features are based on sensor data collected from one person in parallel. In fact the environment and the activity that the participant is engaged in probably causes the features to be highly correlated. This correlation will only sometimes correspond to the expressed emotion, and other times will be due to other actions from the participant. The assumptions of i.i.d. or exchangeable random variables also may not hold because the underlying emotional state of a person while participating in a study could cause a marked change in the responses collected by the sensors.

2.3 Classification Methods

Classification methods involve the categorization of a set of data using either the relationships of samples to each other, unsupervised classification, the relationships of samples to a particular label, supervised classification, or a combination of the two when most labels are missing, semi-supervised classification. For the purposes of this work, a very simple version of supervised classification is used. We create a simple classifier based on the linear regression of selected features and their correspondence to negative and positive examples, where negative labels are set to the value -1, and positive labels are set to the value 1. The classifier predicts based on a linear model, and predictions above 0 are considered to be in the positive class, and in the negative class if predicted otherwise. This simple method allows for very fast computation, it requires very little memory, and it gives a starting point for how well the selected features work together for classification.

The results from constructing a linear classifier, are by no means the final word on how well particular features will work for classifying a set of labelled data, but they do give an answer to the question of what are sufficient features for classifying a set of labelled data. Since the focus of this work is on feasibility of computational affect detection for education and heath care applications, the first step is to find a method that works. Then that method can be built upon with more advanced computational techniques in future work.

CHAPTER 3
USER MODEL FOR COMPUTER BASED EDUCATION

Traditionally, the user model of an intelligent tutoring system (ITS) consists of registration information with or without statistics about interactions with the ITS [67, 115]. Registration information often includes age, gender, class standing, teacher, other static information about learners, and sometimes includes cultural and racial make-up. A limitation of this approach is that the only dynamic information that the ITS uses is based on the cognitive 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 described in Section 2.1.1 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. [10] is an example of having an animated character as part of the tutor giving non-verbal feedback, [53] is an example of a tutor that changes its feedback based on the character's virtual emotional state in response to the student's emotion. For instance, a positive student emotional state elicits happiness in the character, 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. 3.2.2, (2) a pedagogical engine for tutoring the student and collecting tutor data described in Sec. 3.2.1, 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.

3.1 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.

Zhou et al., uses a number of sensors to detect facial expressions, physiological features (heart rate, temperature, and skin conductance), and speech signals [138]. The experiment uses 32 students simultaneously. This application measures emotional responses elicited by the presentation of images rather than from using a tutor system. The emotions that they model are fear, anger, and frustration.

McQuiggan et al., 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 [82, 83]. They create a model of frustration [82] and self-efficacy [83], i.e., the student's belief in producing a correct answer.

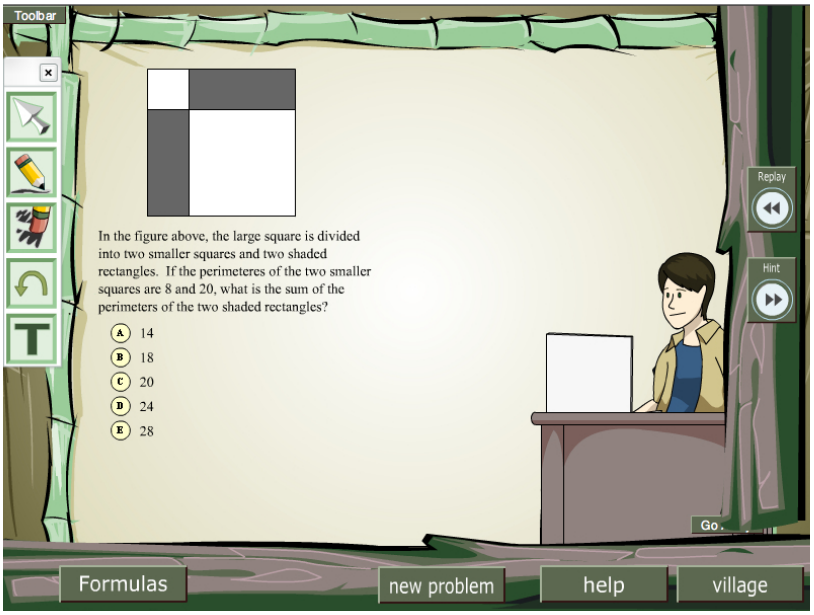
Other work such as Florea and Kalisz, does not use sensors at all, but only uses self reports to determine emotional state [53]. They use three emotional ranges to model the student: boredom vs. curiosity, distress vs. enthusiasm, and anxiety vs. confidence. With the model of the student, they then create 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 [105, 26, 125]. Bringing sensors to our children's schools addresses real problems of students' relationship to mathematics as they learn the subject. This brings new tools to address their frustration, anxiety and disinterest/boredom while learning.

3.2 Affect Detection System

3.2.1 The Tutor: Wayang Outpost

Our test-bed application for the experiments we describe in Sec. 3.3 was Wayang Outpost, a multimedia Intelligent Tutoring System (ITS) for geometry [7]. 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. 3.1.



In the figure above, the large square is divided into two smaller squares and two shaded rectangles. If the perimeteres of the two smaller squares are 8 and 20, what is the sum of the perimeters of the two shaded rectangles?

- Ⓐ 14
- Ⓑ 18
- Ⓒ 20
- Ⓓ 24
- Ⓔ 28

Figure 3.1. 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 [7].

Wayang collects student interaction features in order to predict each student's level of effort on the problems presented. These features, described in Table 3.1, 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.

Table 3.1. 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.

3.2.2 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 3.2. These are used in conjunction with tutor features described in Sec. 3.2.1.

The classifiers in [66] 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.

Table 3.2. 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

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.

3.2.2.1 Mouse Feature

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

$$mousePressure = \frac{\begin{pmatrix} leftMouseFront & + & leftMouseRear & + \\ middleMouseFront & + & middleMouseRear & + \\ rightMouseFront & + & rightMouseRear & \end{pmatrix}}{1023}, \tag{3.1}$$

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.

3.2.2.2 Chair Features

We compute three features from the 6 chair sensors. The first two are based on the most useful features from [38]. These are the net change in pressure of the seat, and the net change in pressure of the back:

$$netSeatChange[t] = \left| \begin{array}{cccc} LeftSeat[t-1] & - & leftSeat[t] & + \\ MiddleSeat[t-1] & - & middleSeat[t] & + \\ RightSeat[t-1] & - & rightSeat[t] & \end{array} \right| , \qquad (3.2)$$

$$netBackChange = \left| \begin{array}{cccc} lastLeftBack & - & leftBack & + \\ lastMiddleBack & - & middleBack & + \\ lastRightBack & - & rightBack & \end{array} \right| , \qquad (3.3)$$

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:

$$sitForward = \begin{cases} \begin{array}{llllllll} 0 & \text{if} & leftBack & > & 200 & \text{or} & & \\ & & middleBack & > & 200 & \text{or} & & \\ & & rightBack & > & 200 & & & \\ 1 & \text{if} & 200 & >= & leftBack & > & -1 & \text{and} \\ & & 200 & >= & middleBack & > & -1 & \text{and} \\ & & 200 & >= & rightBack & > & -1 & \\ \text{NA} & & \text{otherwise} & & & & & \end{array} \end{cases} , \qquad (3.4)$$

where NA is treated as no data.

3.2.2.3 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 used by McQuiggan et al., [83].

3.2.2.4 Mental State Camera Features

Of the six mental state features that the MindReader software identifies, we combine the agree and disagree states into one state about agreement, where the range of [1.0,0.0] of the disagree state is translated to 0.0 to 0.5 of agreeing, and the agreeing state is translated to the 0.5 to 0.1 value of agreeing. 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.

3.2.3 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. 3.2.

In our experiments, we used the student 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 wrist ID pair, and a column

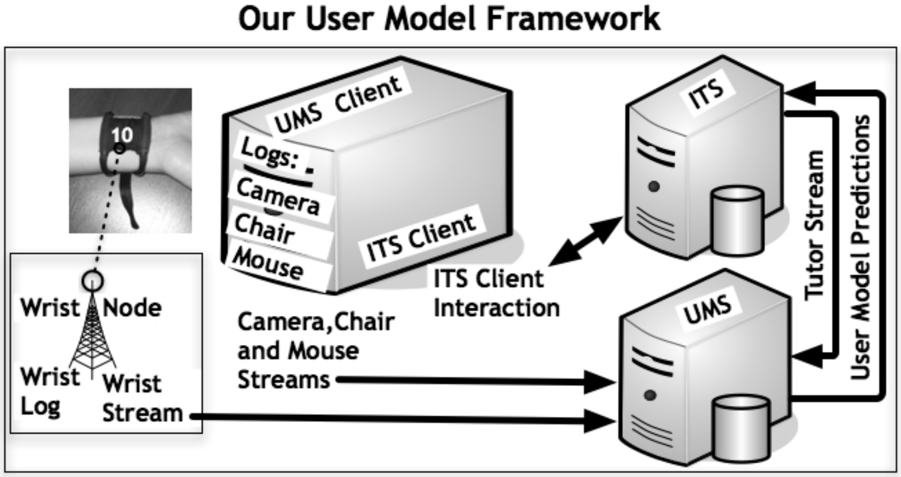


Figure 3.2. A student at the client computer puts on a bracelet and starts the two client programs indicating the wrist ID of the bracelet. The bracelet sends Skin Conductance data to the Wrist Node, then logs bracelet data from all of the students in the classroom. The User Model System (UMS) receives 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.

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 log in or log out 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.

3.3 Experimental Setup

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 came to a lab in the university and used the software for one single session. Wayang worked the same way for all students, as introduced in Sec. 3.2.1, 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. 2.1.1 gathered data on his or her physiological responses.

3.4 Affect Classifiers

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 performed 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 3.4 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 3.4 shows the features selected for each of the linear models. The stepwise linear least squares regression reduces the feature set to at most five of the available features. In addition, only two of the four available sensors are used when creating classifiers from all sensors with the tutor.

Table 3.3. Each cell corresponds to a linear model to predict emotion self-reports. Models were generated using stepwise linear least squares regression, and variables entered into the model are shown in Table 3.4. 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
Confident	$R = 0.44$ $N = 143$	$R = 0.61$ $N = 77$	$R = 0.48$ $N = 115$	$R = 0.40$ $N = 106$	$R = 0.48$ $N = 107$	**R = 0.63** **N = 68**
Frustrated	$R = 0.55$ $N = 138$	$R = 0.60$ $N = 78$	$R = 0.61$ $N = 105$	$R = 0.55$ $N = 109$	$R = 0.59$ $N = 102$	**R = 0.62** **N = 67**
Excited	$R = 0.39$ $N = 154$	$R = 0.40$ $N = 74$	$R = 0.45$ $N = 122$	$R = 0.39$ $N = 106$	$R = 0.45$ $N = 119$	**R = 0.56** **N = 64**
Interested	$R = 0.42$ $N = 133$	$R = 0.56$ $N = 75$	$R = 0.53$ $N = 107$	$R = 0.36$ $N = 101$	**R = 0.67** **N = 102**	$R = 0.66$ $N = 62$

Table 3.4. This table lists the variables that the stepwise regression method selected as relevant, for each of the regression models in Table 3.3. 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 3.1 and 3.2.

	Tutor 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

3.4.1 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 predicted to have a high value of a particular emotion. This prediction could reduce and possibly eliminate the need for querying the user about 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 3.5 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 in which the student does not report a middle rating for their emotion (three). This is likely the case because the middle values indicate indifference.

Table 3.5. This table shows the results of the best classifier of each emotional response (confident, frustrated, excited, and interested). Accuracy of no classifier (last column) is a prediction that the emotional state is always low. 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)

3.5 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 system. Examples of this include encouragement, suggesting that the student ask for a hint, and mirroring the emotion of the student.

CHAPTER 4

RANKING CLASSIFIERS FOR COMPUTER BASED EDUCATION

4.1 Introduction

Student affect plays a key role in determining learning outcomes from instructional situations [11, 69]. For instance, learning is enhanced when empathy or support is present [56, 139]. While human tutors naturally recognize and respond to affect [37, 74], doing so is quite challenging for Intelligent Tutoring Systems (ITS), in part due to the lack of directly-observable information on a student's affect. A promising avenue for increasing model bandwidth, i.e., the quality and degree of information available to a student model, in terms of affect recognition is sensing devices that capture information on students' physiological responses as they interact with adaptive systems. With the advent of inexpensive sensor technology, we have been able to deploy such sensing systems and use their output to infer information on student affect. Specifically, in the Fall of 2008 we performed a number of experiments in the classrooms of schools in both Western Massachusetts and Arizona, with a total of just under 100 students. In each experiment, students were queried about four emotional states (*confident*, *interested*, *frustrated*, and *excited*), providing the standard for validating our models. The study data was used to construct a number of linear classifiers for each emotional state, as we reported in [31]. The best classifiers for a given emotion obtained accuracies between 78% and 87% according to a leave-one-student-out cross-validation.

While these results are promising, it is important to validate the classifiers and verify that their performance generalizes to a new and/or larger population. This is particularly the case for our data, obtained from a classroom setting that involves a higher degree of noise and other distractions than standard controlled laboratory experiments. One aspect of validation involves verifying that our classifiers perform better than the baseline classifier (i.e., one that always outputs yes if the labels are yes most of the time, or no if the labels are no most of the time). In addition to validating our classifier performance, we also wanted to investigate if and how the sensors (or subsets of sensors) improved model performance over using only features from the tutor data (e.g. the number of hints requested). With an understanding of how each combination of sensor and tutor features predicts a given emotion, we can recommend which sensors to use for emotion recognition, and we can also rank the classifiers so that if some sensor data is unavailable, for instance due to an error, a comparable (or the next best) sensor set can be selected.

In this chapter, we report on how we realized these objectives by utilizing a large data set for validation from experiments conducted in the Spring of 2009 with over 500 students. Our results show that our method is successful on three of our four target emotions: for each success, at least one linear classifier performs better than the baseline classifier and generalizes to a new and larger population.

We begin by presenting the related work in Sec. 4.2, and then describing in Sec. 4.3 the setup and apparatus of the experiments used to collect the data. Sec. 4.4 outlines the method for constructing and validating the student emotion classifiers. Sec. 4.5 describes the comparison of classifiers. Sec. 4.6 summarizes the results, discusses the design of affective interventions based on the classifier output, and suggests future work on improving the classifiers.

4.2 Related Work

The results of a feature selection competition in 2004 suggest that feature selection can be very useful for improving classifiers [58]. In addition to using simple correlation coefficients as criteria for selection (as stepwise linear regression does), treed methods, wrapper and embedded methods have been used for feature selection. [38] compares features of a number of individual sensors used for detecting affective state with an ITS, but does not compare disparate sensors, nor are multiple sensors used in conjunction in a classifier. In this chapter, we use a method from [86] to compare and rank the different feature sets used in the linear classifiers as a way of ranking our features selected by stepwise linear regression.

There are a number of adaptive systems in existence that use real-time information about a student in order to address the student's affective state. Recent work includes [30], which discusses the use of electromyogram (EMG) data to improve an affective model in an educational game. This work does careful collection, cross-validation, and uses a pairwise t-test (a parametric test) for ranking the classifiers. [39] aimed to predict learners' affective states (boredom, flow/engagement, confusion, and frustration) by monitoring variations in the cohesiveness of tutorial dialogues during interactions with an ITS with conversational dialogs; here, both student self reports and independent judges were used to identify emotional states. The study compared the correlation between self-reports and independent judges, and used tutor and dialogue features to automatically classify emotion with accuracies between 68% and 78%.

Other work, such as [62, 102], does not incorporate any sensor data to construct affective models. [62] uses Dynamic Bayesian Networks and Dynamic Decision Models specified by an expert to determine and respond to each student's affective state, while [102] uses self-reports to determine affective state and focuses on how affective feedback changes the student's experience. This work does use cross-validation and a parametric ranking for classifiers, but does not do a feature comparison or a validation with a separate population.

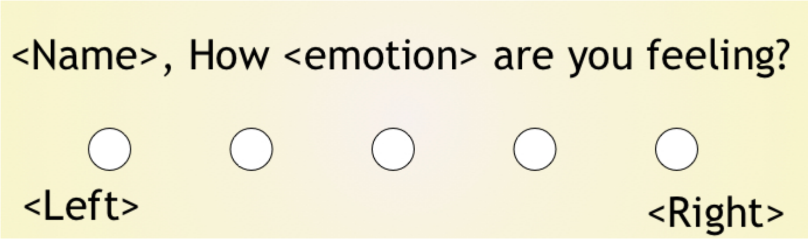
Much of this past research has focused on constructing models based on a fixed set of sensors or solely on expert knowledge. In contrast, our research compares the utility of different sensors as well as sensor and tutor interaction features in a variety of empirically-based models. Another difference relates to the source of the data: Since our data is obtained from actual schools rather than the laboratory, the ecological validity of our results is strengthened. Our features are ranked using non-parametric procedures and take an extra step to validate the results on a separate population in order to address the additional artifacts created by a classroom setting.

4.3 Data Collection: Sensors with Wayang Outpost in the Classroom

4.3.1 Setup

In the Fall of 2008 and the Spring of 2009 the geometry tutor Wayang Outpost was deployed with a set of sensors into real classroom environments [8, 9, 31]. The set of sensors included: a mouse that captured degree of pressure placed on its various points, a bracelet that measured skin conductance of the wrist, a chair that sensed the level of pressure on the chair back and seat, and a camera supplemented with software for facial emotion recognition.

These four sensors collected data on students' physiological responses while students worked with Wayang Outpost. Each student's physiological data and interactions with the tutor were logged. Subsequently, the interaction and sensor data were time-aligned and converted into tutor and sensor features, as described in [31]. At intervals of five minutes in the Fall, and three minutes in the Spring, students were presented with an emotional query about one of four affective states (*confident*, *interested*, *frustrated*, or *excited*) selected from a uniform random distribution. The queries were presented as shown in Fig. 4.1; to respond, students selected from the options shown in Table 4.1. The sensor and tutor features were used as predictors for the levels of the self-reported affective states.



<Name>, How <emotion> are you feeling?

○ ○ ○ ○ ○

<Left> <Right>

Figure 4.1. An example of the Emotion query. Table 4.1 below has the values for each <> enclosed word, except for (<*Name*>), which is the name of the student.

Table 4.1. The mapping of tags to text in Fig. 4.1 above.

<emotion>	<Left>	<Right>
confident	I feel anxious	I feel very confident
interested	I am bored	I am very interested
frustrated	Not frustrated at all	Very frustrated
excited	I'm enjoying this a lot	This is not fun

The Fall 2008 data collection involved 93 students using the Wayang Tutor. Of the 93 students 85 of them had at least one working sensor connected to them while using the tutor. Students used the tutor as part of a class, and class sizes ranged from three to twenty-five students with one teacher in the classroom and between one and three experimenters. The students had between two and five sessions with Wayang Outpost, based on teacher preference and availability of the student. The student ages were 15-16, 18-22, and 22-24. These data were used as our training set.

The Spring 2009 data collection involved over 500 students using the Wayang Tutor. 304 of the students were connected to at least one working sensor. The Spring collection differed from the Fall collection as follows: (1) The students in the Spring were from different schools; (2) The ages of Spring students were 13-14, and 15-16;

(3) The camera sensor in the Spring had upgraded software. The Spring Data was used purely for validation of the Fall Data.

4.3.2 Tutor and Sensor Features

We considered nine tutor features and forty sensor features as potential predictors for the emotion classifiers (see Table 4.2). The forty sensor features are based on four ways of summarizing ten specific features: the mean, the standard deviation, the min value, and the max value over the course of a problem. Since the sensor and tutor logging happens asynchronously, their data are interpolated in a piecewise constant fashion with the constraint that only data from the past is used to predict missing sensor or tutor values. The tutor logs when a problem is opened and closed, creating boundaries for summarizing the interpolated sensor data (i.e. to compute each feature, we use data over the span of a single problem). When there is an emotional query after a problem, the result becomes the affective state label for that problem. For each student and for each emotion there are between two and five affective-state labels. For more detail on the full specification of these features see Chapter 3.

4.4 Method

The current standards for evaluating affective classifiers do not address our need to rank classifiers for the purpose of actionable affect detection. Though each individual step in our method has been established and tested, the combination of these steps yields a more robust test for the classifiers constructed. The use of our classifiers in a classroom environment necessitates our method described in the rest of this section and summarized in Table 4.3.

Table 4.2. Features used for each problem that includes an affective state label in order to train the emotion classifiers (features are shown in abbreviated form). The nine tutor features are shown on the left and the ten sensor features are on the right. Features used in a classifier that are significantly better than the baseline ($p < 0.05$) are in **bold**.

Tutor feature	Definition
Solv. on 1st	1st attempt correct
Sec. to 1st	time to 1st attempt
Sec. to solv.	time to a correct
# incorrect	responses
# hints	requested
LC	learning companion
Group	which LC (Jake, Jane, or none)
Time in session	same day
Time in tutor	all days

Sensor feature	Definition
Agreeing	camera mental states
Concentrating	
Thinking	
Interested	
Unsure	
Mouse	sum of pressure
Sit Forward	movement in chair
Seat change	
Back change	
Skin conductance	value from wrist

4.4.1 Collection

The data collection described in Sec. 4.3 is the first step in our methodology for building affect classifiers. The key parts of the data collection are that the emotion labels are made at the time of the experience, and the training and validation sets are taken from distinct populations using the same basic setup, allowing the validation results to be more likely to generalize. Here, the Fall collection is our training data set and the Spring collection is our validation data set.

4.4.2 Predictor Selection

Once the data were collected and summarized as described in Sec. 4.3.2, we used the entire set of labeled training data to create a subset of predictors using a combination of tutor and sensor features. For each combination of features, a subset of the data set that was not missing data for the features was selected. Then stepwise linear regression was performed in R, an open source statistical package [98], to select the 'best' subset of features from those available. The subset of features was stored as a formula for use in training the classifiers and performing cross-validation.

4.4.3 Cross-Validation

For each set of features determined by the feature selection, we performed leave-one-student-out cross-validation on linear classifiers for each affective state. During the cross-validation, we calculated the mean accuracy, sensitivity, and specificity for each test student. We also performed the same cross-validation on a linear classifier with a constant model, which we used as our baseline. This step differs from [31] in two ways: 1) The mean was taken across each test student instead of across tests. 2) We calculated sensitivity and specificity in addition to accuracy.

Though the cross-validation described above provides a general indication of the performance of each classifier, the information is not sufficient to enable appropriate pedagogical action selection by an ITS for *new* populations of students. Thus, we validated that the classifiers are generalizable and so can be used with a new population without having to be retrained. We also ranked the classifiers according to how sensors and features impact accuracy, allowing us to make informed decisions about sensor selection (e.g., if some sensors become unavailable, to select the next best alternative).

4.4.4 Classifier Ranking

A number of alternative techniques exist for classifier comparison. One is to use classifier accuracy, which identifies the overall performance of a classifier, but does not express accuracy on positive vs. negative instances. To do so, the following two measures can be used: (1) sensitivity, also referred to as the true positive rate, which provides information about the accuracy of a positive response; (2) specificity, the true negative rate, which provides information about the accuracy of negative responses.

Since the purpose of our classifiers is to help an ITS make decisions of how to appropriately respond to student emotion, one approach would be to only make a decision when there is confidence in the prediction. So, if one classifier has very good sensitivity relative to the baseline, then the ITS would act when the classifier reports a positive result. Similarly, if a classifier has a very good specificity relative to the baseline, then the ITS would act when the classifier reports a negative result.

In order to compare our classifiers' accuracy, sensitivity, and specificity for each affective state, we first performed a one-way analysis of variance (ANOVA), with each classifier as the independent variable and either accuracy, sensitivity, or specificity as the dependent variable. When there was a significant difference between classifiers, we performed Tukey's HSD test to rank the differences in the means. Tukey's HSD test is a parametric multiple comparison test to find which means are significantly different from each other [126].

There is some question about the soundness of the ANOVA and Tukey's HSD test for these comparisons because the design is not balanced (not every student had all sensors available), and the responses are not normally distributed. So, in addition to the ANOVA, a Kruskal-Wallace test was performed; when there was a significant difference between classifiers, a nonparametric multiple comparison procedure (NPMC) for an unbalanced one-way layout was performed, as described in [86].

We conducted both parametric and non-parametric tests because the parametric tests are known to be robust to violations of the assumptions, so performing both was a way to verify the findings. Here, for all tests, we only report results with significant differences.

4.4.5 Validation with Follow-on Data

As mentioned above, we used the Spring 2009 data set to validate the classifiers trained on the Fall 2008 data set (the Spring data set was not used to inform any of the training). The validation consisted of the following three steps. First, for each feature set selected by the feature selection step, a linear classifier was created using the entire subset described in Sec. 4.4.2. Second, each classifier was tested on the relevant subset of data from the Spring data set. Third, the accuracy, sensitivity, and specificity values and rankings were compared to the cross-validated values and rankings to determine how the classifiers generalized to a new and larger population.

4.5 Results

The classifier sets were designed to compare the performance of (1) a classifier using just tutor features vs. (2) one using features from one sensor in addition to the tutor features vs. (3) a classifier using all of the available features. The collection, feature selection, and cross-validation results from the training data (Fall 2008) are described in Chapter 3 [31]; however, a couple of important details are needed here.

Table 4.3. Summarization of the affect detection method.

1. Data Collection
    - in situ self-reports by students of emotion
    - training and validation sets from different populations
2. Feature Selection
    - remove central self-report values
    - use step-wise linear regression to select features and train classifiers
3. Cross-validation (leave-one-student-out)
    - compute the mean accuracy, sensitivity, and specificity per student
4. Classifier ranking
    - parametric and nonparametric ranking using $p < 0.05$
5. Validation
    - run Steps 3 and 4 on validation set using classifiers from Step 2

First, although the feature selection has the option of using both tutor data and other sensor data, sometimes it only selected tutor data. Table 4.4 shows the results of the feature selection. Second, we extended the cross-validation results to include sensitivity and specificity. Third, we modified the grain size, in that the samples in this work are on a per student rather than per test basis. The ranking and validation results are discussed below.

Table 4.4. These are the results of the feature selection. The baseline classifier for each emotion is just a linear model trained on a constant. The classifier names are the concatenation of an abbreviated emotion (e.g., confident, interested, and excited) and the contributing sensor features. If there are no sensor features, then Tutor comes after the emotion, and when there is more than one classifier with the same feature set a letter is added to disambiguate the names (e.g. TutorA is only tutor data, and TutorM is only tutor data, but the stepwise selection process had the mouse data available, but no mouse features were selected). Names in **bold** are for classifiers that performed significantly better than the baseline for that emotion in at least one way.

Classifier name	Features
confBaseline	constant
confTutorA	Solv. on 1st + Hints Seen
confTutorM	# Incorrect + Solv. on 1st + Session
confSeat	# Incorrect + Solv. on 1st + sitForward Std. Dev.
intBaseline	constant
intMouse	Group + # Hints + mouse Std. Dev. + mouse Max
intCamera	Group + # Hints + interestedMin
excBaseline	constant
excTutor	Group + # Incorrect
excCamera	interested Mean + # Incorrect
excCameraSeat	netSeatChangeMean + interestedMin + sitForwardMean

4.5.1 Classifier Ranking

Accuracy had a significant main effect on both the *interested* and *excited* affective states, but not for the *confident* and *frustrated* states. For the *interested* state, the classifier using the mouse and tutor features is significantly better than the baseline with a mean of 83.56% vs. 42.42%, according to both Tukey's HSD and NPMC tests.

For the *excited* state, the classifiers with the tutor features were significantly better than the baseline with a mean of 73.62% vs. 46.31%.

As far as sensitivity is concerned, there is a significant main effect for *confident*, *interested*, and *excited* affective states using both parametric and nonparametric tests. However for *confident*, no classifier performed better than the baseline. For *interested*, both the camera and tutor, and mouse and tutor features were better than the baseline. For *excited*, the camera with seat sensors, camera sensors, and tutor only performed better than the baseline.

For specificity, there is only a significant main effect for *confident*, with TutorA, TutorM, and Seat classifiers performing better than the baseline. The details of these results are shown in Table 4.5.

Table 4.5. Classifier ranking using cross-validation data ($p < 0.05$).

Confident	Tukey HSD	NPMC
Specificity	$(confTutorA \sim confTutorM \sim confSeat) > confBaseline$	$(confTutorA \sim confTutorM) > confBaseline$

Interested	Tukey HSD	NPMC
Accuracy	$intMouse > intBaseline$	$intMouse > intBaseline$
Sensitivity	$(intCamera \sim intMouse) > intBaseline$	$(intCamera \sim intMouse) > intBaseline$

Excited	Tukey HSD	NPMC
Accuracy	$excTutor > excBaseline$	$excTutor > excBaseline$
Sensitivity	$(excTutor \sim excCamera \sim excCameraSeat) > excBaseline$	$(excTutor \sim excCamera \sim excCameraSeat) > excBaseline$

Given these results, our findings suggest that the tutor could generate interventions more reliably when it detects interest and excitement. If the authors wanted the tutor to intervene when the student is *interested*, then using the mouse and tutor features or the camera and tutor features would be most appropriate. If the authors wanted the tutor to intervene when the student is *excited* then either the camera with seat features, camera features, or tutor features classifier would all be appropriate.

It may be more relevant to intervene when a student is not *interested* or not *excited*, or not *confident*. Our results do not provide information on which features to use to predict low interest or low excitement, but to detect lack of confidence, we could use either the TutorA, TutorM, or Seat features trained on *confident*. The corresponding features are shown in Table 4.4.

4.5.2 Validation with Follow-on Data

In order to verify that our classifier ranking generalizes to new data sets, we tested the classifiers by training them with all of the Fall data and testing them with the Spring data. Performance results of the significantly ranked classifiers from the cross-validation done above are compared to the validation set and shown in Table 4.6. Since the data are from an entirely separate population, it is likely that the overall performance will degrade somewhat; however, if each classifier's performance is similar, then that will provide evidence that the classifiers should be preferred as they were ranked during the cross-validation phase.

When comparing mean accuracy for the training vs. test sets, there is a general drop in accuracy of between 2% and 15%, though in some cases, there is a much larger difference of up to 37%. The larger differences suggest that some of the features do not generalize well to new populations.

Results of ranking the classifiers on the validation data are shown in Table 4.7. Note that the accuracy rankings no longer hold, and the mouse classifier for the *interested* affective state is no longer significantly better than the baseline.

4.6 Discussion

In this chapter we describe a method for discovering actionable affective classifiers for Intelligent Tutoring Systems (ITS). Though the method was used with specific

Table 4.6. This shows validation results of all classifiers that performed better than the baseline classifier during training. All values are the mean value per student. Fall specifies the training set based on the leave-one-student-out cross-validation, and Spring specifies the results of the classifiers trained on the training set (Fall 2008 Data), and tested on the validation set (Spring 2009 Data). Values in **bold** are significantly better ($p < 0.05$) than the baseline.

model	Accuracy		Sensitivity		Specificity	
	Fall	Spring	Fall	Spring	Fall	Spring
confBaseline	65.06%	62.58%	72.22%	76.13%	55.56%	44.14%
confTutorA	70.49%	65.49%	47.07%	46.04%	**90.43%**	**84.88%**
confTutorM	68.64%	67.53%	52.31%	52.26%	**82.41%**	**80.68%**
confSeat	65.70%	67.13%	54.63%	60.17%	**79.26%**	**70.32%**
intBaseline	42.42%	78.30%	0.00%	0.00%	81.82%	100.00%
intMouse	**83.56%**	63.34%	**29.73%**	5.09%	90.54%	81.60%
intCamera	69.44%	57.65%	**52.08%**	**12.11%**	64.58%	68.53%
excBaseline	46.31%	74.31%	0.00%	0.00%	96.15%	100.00%
excTutor	**73.62%**	62.99%	**36.54%**	**12.45%**	87.88%	77.28%
excCamera	66.33%	51.53%	**38.67%**	**28.39%**	72.00%	52.24%
excCameraSeat	70.67%	43.34%	**32.00%**	**15.97%**	83.00%	54.07%

Table 4.7. Classifier ranking using validation data from the Spring of 2009. All differences indicated by '>' are significant with $p < 0.01$.

Confident	Tukey HSD	NPMC
Specificity	$(confCameraA \sim confTutorA \sim confTutorM) > (confSeat \sim confTutorW) > confBasline;$ $confCameraB > confTutorW > confBaseline$	$(confCameraA \sim confTutorA \sim confTutorM) > (confSeat \sim confTutorW) > confBasline;$ $confCameraB > confTutorW > confBaseline$

Interested	Tukey HSD	NPMC
Sensitivity	$intCamera > intBaseline$	$intCamera > intBaseline$

Excited	Tukey HSD	NPMC
Sensitivity	$((excCamera > excTutor) \sim excCameraSeat) > excBaseline$	$excCamera > excCameraSeat > excTutor > excBaseline$

sensors, features, ITS and classifiers based on linear models, each of these could conceivably be swapped out for another system.

Our results identify a clear ranking for three classifiers designed to detect low student confidence, one classifier to detect interest, and three classifiers to detect excitement. For not *confident*, two different sets of tutor only features performed better than the tutor and seat features, so it is unlikely that there would be a time that we would use the classifier with the seat sensor.

Now that we have actionable classifiers for three affective states, our ITS will be able to leverage the results to make a decision. For instance, the ITS could intervene whenever the classifier detects low student confidence, in order to help the student gain self efficacy. This intervention will have to also take into account other emotions detected, e.g., the detection of high excitement and/or high interest may change the type of intervention that is most appropriate.

Future work will involve implementing these various affect-based interventions, and evaluating their impact on student learning, affect and motivation. We also plan to explore how we can design classifiers for affect recognition that perform better than the baseline for the subset of affective states on which our classifiers performed poorly. One approach for doing so that we plan to implement is to identify more complex features based on the sensor data than those currently used. A more complete set of affective classifiers will likely improve the ITS interventions. For example, if we had a classifier that had good sensitivity for confidence, then that classifier could be used to stop interventions relating to low confidence.

CHAPTER 5
SPEAKER DIFFERENCES AND HEALTH DIAGNOSIS

The intersection of emotion and health is most clear in voice production, and the field of communication disorders utilizes the voice for diagnosis of a variety of problems. One of the oldest recorded voice related communication disability was that of Mursilis, a Hittite king from 1344-1320 B.C.E. [41]. In a cuneiform text, Mursilis describes his fear causing his loss of speech a number of times during his life.

With the creation of the telephone, tools became available to study voice [34], and since the early twentieth century empirical studies of specific vocal features such as pitch and intensity have been studied in relation to emotion, such as differentiation between feeling happy and sad [118], and health, such as what is typical [88], characteristics of Parkinson's [24], and characteristics of a cleft palate [63].

5.1 Related Work

McCauley and Strand performed a review of standardized tests to diagnose childhood apraxia of speech (CAS) and found that the tests do not adequately address "relevant psychometric principles" [79]. The two metrics that are commonly used to aid in the diagnosis of CAS are the lexical speech ratio (LSR) [113], and the coefficient of variation ratio (CVR) [114]. There is a proposed computational method for diagnosis of CAS with these two features [64], however this method still requires the manual time alignment of phonemes from each subject. Since this is a labor intensive process, fully automated computational methods are desirable.

The diagnosis of Austistic Spectrum Disorders (ASD) involves many methods including evaluating voice production [52]. McCann and Peppe reviewed studies involved with the symptom of unusual prosody in Autism Spectrum Disorder (ASD) to determine if a standard quantitative measure has been established, and they found a lot of disagreement in the literature [78]. Since then, Velleman, Andrianopoulos, et al., studied differences in children with neurodevelopmental problems such as CAS and ASD, and noted significant differences in motor speech and voice between these two groups and their typically developing peers [127]. In addition, Paul et al., conducted a study on both the perception and production of prosodic features [94]. The authors found that there were significantly more errors for ASD subjects than typically developing (TD) subjects when it came to producing the correct lexical stress. Specifically when given the instructions to pronounce the word recall as "re **call**" as opposed to "**re** call" when reading the sentence "I can't recall his name."

There have been a number of computational approaches to distinguish pathological voices from healthy voices. One example is Fonseca et al., who use linear prediction coefficients (LPC) and a discrete wavelet transform (DWT-db) with a least square support vector machine to determine whether a patient has a pathology, nodules or vocal folds, or whether the patient is healthy [54]. In addition, some work has been done to automatically detect negative symptoms in schizophrenia [29]. The authors used the standard deviation of F_0 during a 50 ms frame as the inflection. Alogia, or poverty of speech, was computed as words per minute, or total word count divided by total time of patient speaking. Additionally computerized lexical analysis was done after the data was transcribed by human laboratory assistants.

We use non-lexical acoustic features that have been used in the past as well as novel features for the computational classification of gender and different cultures.

5.2 Experimental Setup : Multicultural Study

In the current multicultural study, ten participants were studied, comprised of 5 males and 5 females per culture/race. Mandarin Chinese, Hindi Indian, Caucasian American, and African American males and females were matched within 15% by age, height, and weight. Acoustic measures of each participant were collected in a sound proof room to minimize contamination of the acoustic signal due to ambient noise levels. Participants' voices were recorded using a TASCAM DA-P1 DAT recorder and a condenser microphone positioned one inch and 45° off axis from the participant's mouth. More detailed information about the highly controlled conditions can be found in work from 2001 of Andrianopoulos et al., [5, 6]. Participants performed a number of speech tasks. Tasks included vowel production and spontaneous speech. The vowels, [*a*] (as in the word 'ah'), [*i*] (as in the word 'eat') and [*u*] (as in the word 'glue'), were selected for the study because they are universal across cultures. Three tokens of 600 ms were obtained for each vowel. The spontaneous speech samples were obtained in order to analyze connected speech characteristics. The order of the tasks was as follows:

1. Pronounce three prolonged vowels:

   [*a*] (as in the word 'ah')

   [*i*] (as in the word 'eat')

   [*u*] (as in the word 'glue')

2. speak demographic information in English

3. speak demographic information in native language

4. describe picture 1 in English

5. describe picture 2 in English

6. describe picture 1 in native language

7. describe picture 2 in native language

5.3 Classification

There are a number of ways to categorize speakers from the multicultural data. It is less challenging to identify speakers by gender. It is desirable to identify those features that distinguish between each culture and race; however, this is a four class classification problem, and it's much less likely that simple linear least squares regression will do well for this number of classes. Another way to split the data is by native English speakers vs. non-native English speakers.

The multi-class version of the simple linear least squares classifier actually requires that four separate classifiers are trained, and the class is selected by which classifier gives the highest score. There are some potential problems with this approach when applying it to simple linear least squares models; however, the basic method for multi-class classification is the same.

The acoustic features that we use for classification are derived from pitch, intensity, and time and are shown in Table 5.1.

Features are collected by first segmenting the speech files of each subject into utterances. The utterances are defined by different length pauses, where a pause is defined by the intensity of the recording going and staying below 60 dB for a specific length of time. The pause length minimums that we check are 100 ms, 150 ms, 200 ms, 500 ms, 800 ms, 900 ms, 1000 ms, 1100 ms, and 1200 ms. For each pause length we either add a 100 ms buffer on either side of the utterance (if there is space to do so) or we add no buffer to the utterance. The addition of the buffer increases the size of the utterance, but does not modify the sound in any way.

Once we have each of the utterances, prolonged vowels and unspoken sounds were automatically removed from the set of utterances using a heuristic as follows. If

Table 5.1. The ten acoustical features below are selected by using a linear least squares stepwise regression models to predict gender, American vs. Asian culture, or one of four cultures. This table lists each feature with an abbreviation and a definition.

Feature	Abbreviation	Definition
Pitch Mean Hz	$mean_{F_0}$	The mean F_0 of the utterance in Hz.
Pitch Stdev Hz	$stdev_{F_0}$	The stdev F_0 of the utterance.
Pitch Min Hz	min_{F_0}	The min F_0 of the utterance.
Pitch Max Hz	max_{F_0}	The max F_0 of the utterance.
Pitch Change	$change_{F_0}$	The mean absolute slope of F_0 in Hz of the utterance.
Intensity Mean dB	$mean_I$	The mean I of the utterance.
Intensity Stdev dB	$stdev_I$	The stdev I of the utterance.
Intensity Min dB	min_I	The min I of the utterance.
Intensity Max dB	max_I	The max I of the utterance.
Ratio Voiced	$\%_{voiced}$	The ratio of voiced to total number of frames in the utterance.

the $\%_{voiced}$ feature is between 20% and 80%, then it is considered natural speech. Otherwise it is discarded. This was done because the natural speech data is more relevant for other studies that record natural speech rather than scripted speech that is ideal for data collection. We use the same method of stepwise linear least squares regression and leave one subject out cross-validation on a linear least squares classifier as we do for the Computer Based Education work described in Chapter 3.

5.4 Results

The gender classifiers performed best when the utterances were defined as being separated by pauses of at least 150-200 ms with no buffer. Figure 5.1 shows the relationship of minimum pause time differentiating utterances and the classification accuracy. Accuracies range from 84% to 93%. The features selected for gender that serve as the best classifiers were: $mean_{F_0}$, $stdev_{F_0}$,max_{F_0},min_{F_0},$mean_I$,max_I,$stdev_I$, and $change_{F_0}$ as defined in Table 5.1.

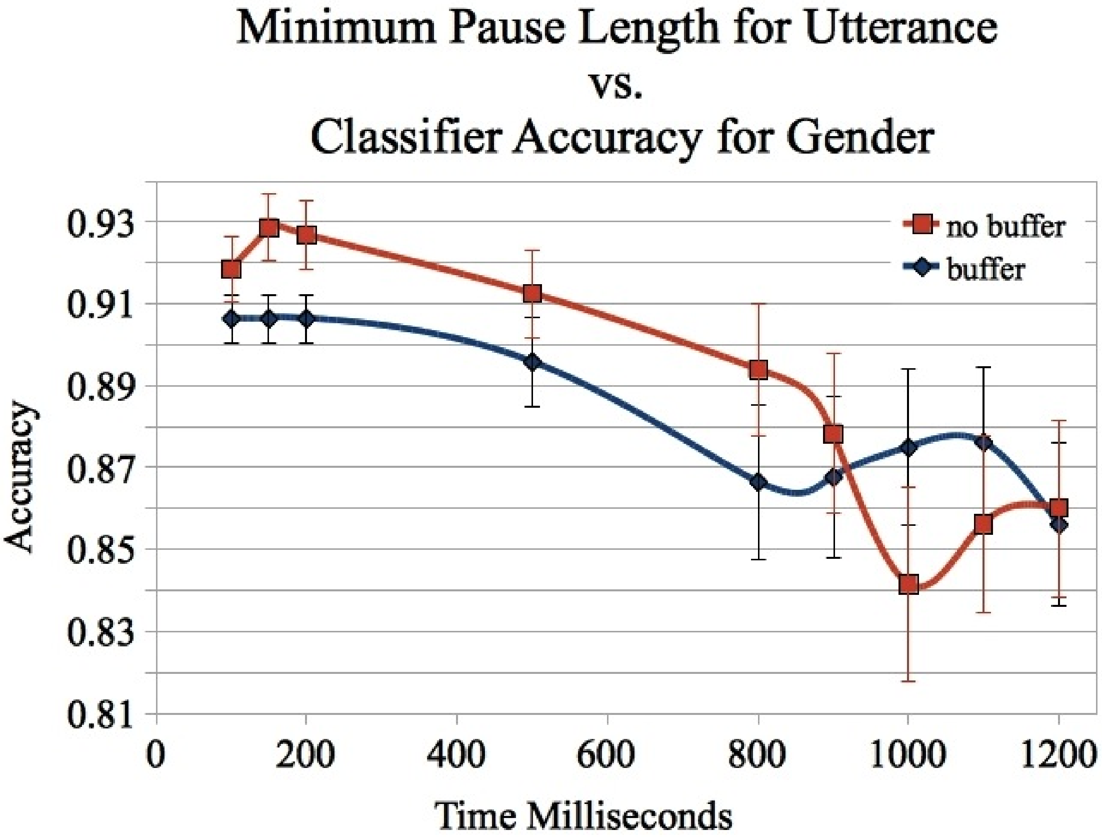


Figure 5.1. The effect of pause length on extracting useful utterances for the classification of gender. The red line with boxes expresses utterances extracted with no buffer, and the blue line with diamonds expresses utterances extracted with a 100ms silence buffer on each side. 95% confidence intervals are shown.

The multi-class classifiers for culture did not perform nearly as well using the same initial set of features from Table 5.1. Since there are four classes of equal size, the baseline accuracy is 25%, and the classifiers perform between 18% and 29% on male voices, and between 19% and 30% on female voices.

The American vs. Asian classifiers for culture did better than the multi-class classifier with accuracies for male speakers of 59% - 69%, which is almost a 20% increase over the baseline. The accuracies for female speakers were between 59% and 70%. The lower performance of the multi-class classifier is likely related to the inherent trouble of using a linear least squares model for multiple classes. Figure

5.2 shows the accuracy of the two class culture classifiers. Separate classifiers are shown for males and females. The confidence intervals for the classifiers increases significantly for 500 ms and above.

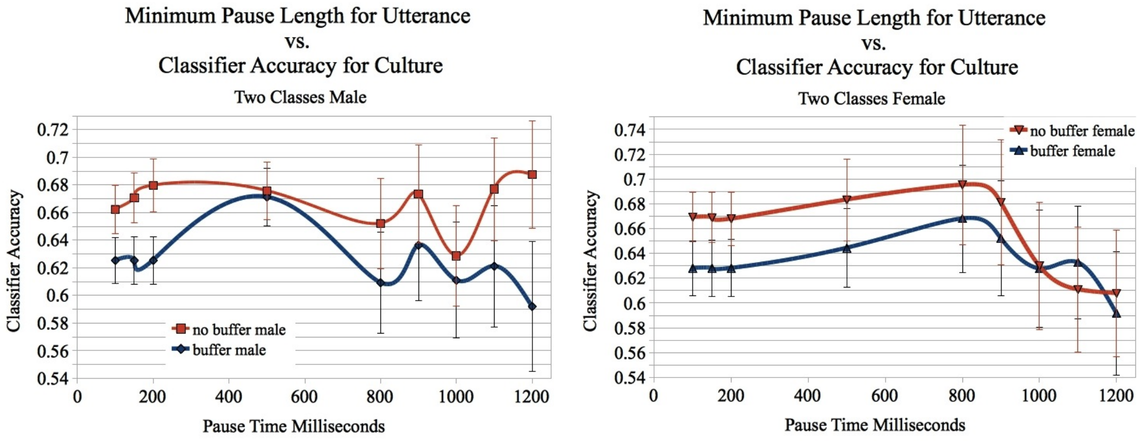


Figure 5.2. The effect of pause length on extracting useful utterances for the two class classification of culture (American vs. Asian). The left shows the results for male subjects. The red line with boxes expresses male utterances extracted with no buffer, the blue line with diamonds expresses male utterances extracted with a 100ms silence buffer on each side. The right shows results for female subjects. The red line with down triangles expresses female utterances extracted with no buffer, the blue line with up triangles expresses female utterances extracted with a 100ms silence buffer on each side. 95% confidence intervals are shown.

5.5 Discussion and Future Work

The results of the multicultural study are promising for the construction of fully automated tools for classification using voice data. The results build on the previous work that used the same data set, by adding automatic extraction of free speech utterances from the participants' raw recordings. We were able to use pitch and intensity features in order to distinguish gender with up to 93% accuracy, and between American vs. Asian with up to 70% accuracy. In addition, for the gender data we found a significant difference in classifier accuracy as the minimum pause length changes between 200 ms and 500 ms. This suggests that the optimal pause length to automatically segment speech is between 100 and 200 ms.

A linear least squares classification for the multi-class culture categorization was insufficient. This is likely due to two explanations: 1) linear least squares classification is known to have difficulty with more than two categories; 2) the number of subjects in each class is two small to find the differences that would be readily apparent. A third explanation would be that the features available are not useful for categorization of cultural differences. However, if this were the case then the two class version of the culture classifier wouldn't have performed well.

The fact that the features selected for both culture and gender were very similar is problematic for the goal of finding independent features for each type of categorization. The one feature that was selected for gender, but was not selected for culture differentiation is $\%_{voiced}$. This feature is a good place to start. In addition, we only looked at the statistics of individual utterances, and we did not look at the sequence of utterances and how they change over time. A future step is to study how utterances change over time. However, we anticipate difficulties with this approach as the sequence lengths get longer, since there will be fewer samples per participant. In addition, increasing the number and type of variables for study may increase the accuracy and validity for these analyses. For example, this research only studied pitch (fundamental frequency) and other analyses of measurements on pitch signals and intensity. It is prudent to study other features of the acoustic signal, such as differences in short- and long-term frequency and amplitude perturbation, especially for health diagnosis, noise to harmonics ratio, percent tremor, soft phonation index, and number of semitones, to name some. Many of these named features are typically evaluated on prolonged vowel data or on phrases that are identical, so new methods are needed in order to apply them to the free speech samples in question in this research.

CHAPTER 6

HEALTH CARE EDUCATION

Health Care education includes a practical component that does not easily translate to a typical computer tutoring system. For example, in a practical scenario for a nurse in training, the student must be able to physically interact with the patient in order to learn the appropriate response to a patient's needs. Clinical simulation environments are often used in order to reduce the number of people required to train a nurse while allowing them to receive practical experience before interacting with real patients [109, 95, 59]. These simulation environments are used for the evaluation of the student nurses. During the evaluations, student nurses are video and audio recorded. This video and audio recording is a place where computational assistance can be given to the instructors. In this chapter we present computational detection of emotion in a clinical simulation to help an instructor determine if a student is at a higher risk of leaving the program. We discuss clinical simulation, video detection of emotion, audio detection of emotion. Then we describe an experiment involving student nurses self-reporting their emotion before and after their clinical evaluation. Finally, we show the results of detecting affect in the above mentioned experiment.

6.1 Clinical Simulation

Since the 1960's, mannequins have been used for medical training [32]. The first success is Resusci®-Anne, which was made so that people could learn mouth to mouth ventilation. Many different mannequin systems have been created with a variety of acceptance. Recently, the clinical simulation has been added to the curriculum of student nurses [95, 59]. One skill that is practiced with these simulators is a ten minute patient assessment [133], in which the student nurse is evaluated while interacting with a simulated patient. The student nurse is in a room alone with the simulated patient. The instructor remotely provides the voice of the patient in the room and the doctor on the other end of the phone. There are realisitic props that are typical in a hospital room, including a monitor, a method for providing air to the patient, and a way to provide intravenous (IV) fluids to the patient. In addition, the mannequin produces sounds like a heartbeat and breathing when observed with a stethoscope. The limbs can also show ailments on them. The clinical simulation labs are fitted with a camera and microphone so that students in a classroom can watch the simulation, and/or the simulation can be recorded on DVD for future viewing.

As students become more familiar with the simulator, they watch a video of their own evaluation as part of the evaluation process, after which they discuss their performance with the instructor.

6.2 Experimental Setup

52 subjects were recruited for the study, 3 students left the study leaving 4 male and 45 female subjects. Subjects were all in a four-year undergraduate bachelor of science program for preparation to become registered nurses. Subjects were either in their third or fourth year of the program. This study involves giving two surveys, one before and one after the simulation test. In addition, the DVD recording of the simulation test that is already used as part of the student's test, was collected and archived for computational analysis. The order of the protocol is as follows: Subjects were briefed on the study. A pre-test survey of emotion was given to the subjects. Subjects took their simulation test while being recorded in video and audio on a DVD. A post-test survey of emotion was given to the subjects. Subjects performed a self-assessment by viewing the DVD of their test. Subjects discussed their performance

with their teacher. DVDs and surveys were collected at the end, and students were debriefed in case they had any questions or concerns. Of the 49 subjects one subject withdrew from the experiment, and one subject did not complete the post-test survey.

6.3 Video Features

The goal of this study was to determine whether the location and activity of the student nurses, as extracted by state of the art computer vision algorithms, are useful for the detection of emotions related to learning environments. The emotions that are in question were confidence, anxiety, interest, excitement, and frustration.

Due to the setting of the study, video recordings are different from most studies involving using video to detect emotion, and it was also different from most studies involving tracking a person. The first major difference in this study was that the face of the subject was rarely, if ever, in view of the camera. This precluded the use of facial expression analysis for the purpose of emotion. The second major difference was that there are no markers or other ground truth information for tracking. In some studies, when there are no markers used, and no ground truth information for position, the person being tracked wore clothing of a color in high contrast to the background, and the room had a background color that was different from the skin tone and clothing of the subjects.

Given that the subjects were being evaluated by their instructors, the environment could not be changed to make it easier on the vision algorithms. This meant that the students were wearing white shirts in a room painted off-white, and with off-white linens.

The lack of ground truth information for the tracks meant that the tracking algorithms were evaluated qualitatively, and a number of competing tracking algorithms were used to get the distances to key points at each frame.

The video data was processed by tracking the nurses position, and then identifying which point of interest the student was engaged with at the time. From there, the proximity and activity were used to identify parts of the PICI scale defined by Bierman.

6.3.1 Feature Extraction

One method of extracting features from emotion, first done by Schlosberg [110] and later refined by Feldman [50] was to categorize an emotion on a two dimensional scale regarding the valence (i.e. positive vs. negative) and the arousal (i.e. low vs. high activity) of the emotion. A similar method for emotion during interaction, proposed by Bierman [15], involved a 2 dimensional scale of accepting vs. rejecting and activeness vs. passivity. This scale was called the Personal Interaction Coding Inventory (PICI). We hypothesized that PICI related features in the video would help to predict or classify the self-reported emotional state of the student.

In order to test this hypothesis we defined 3 key points of interest, as shown in Figure 6.1 and collected features related to the PICI scale. We first collected the distance from the predicted head position of the person to each key point. These distances were binned such that at each time step, the closest distance was binned to the closest key point. With each of the three bins, basic statistics (mean, min., max., and std. dev.) of the distances were taken. In addition, the size of each bin and the number of switches to another bin were computed.

This yielded 18 features, six for each location. The min, mean, and max distance as well as the amount of time near the location related to proximity which loosely corresponded to the accepting vs. rejecting axis of the PICI; and the std. deviation of the distance and number of switches between bins loosely corresponded to the activeness vs. passivity axis of the PICI.

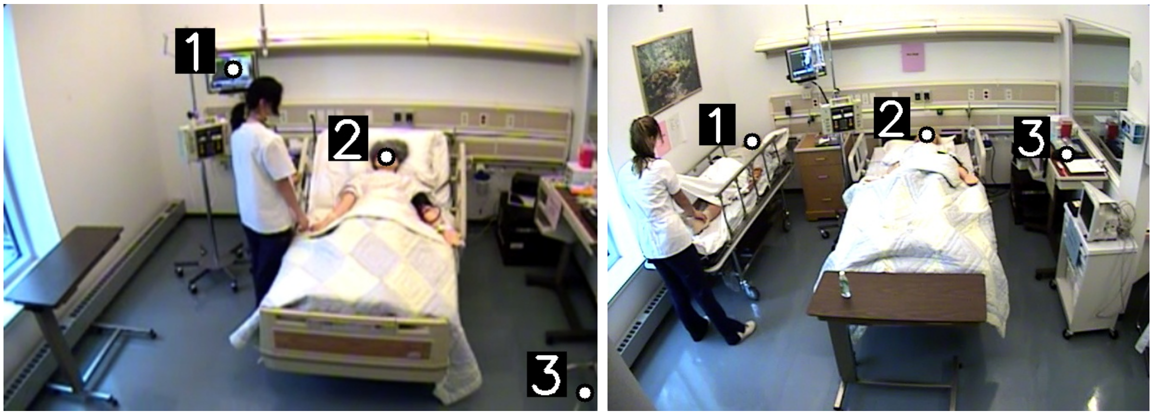


Figure 6.1. Left: The key points for Group A with one simulated patient. The key points in this room were 1) The monitor, 2) the patient, and 3) the telephone. In this frame, the student is closest to the monitor, but actually interacting with the patient. Right: The key points for Group B with two simulated patients. The key points in this room were 1) patient 1, 2) patient 2, and 3) the telephone. In this frame the student is closest to patient 1.

6.3.2 Affect Classification

The 18 video features were then tested to see how well they correlate with the self reported emotions during the evaluation. The five affective states that were reported by the students are (confidence, anxiety, frustration, interest, and excitement). These emotions were reported by selecting from five phrases of increasing level of the emotion. For instance, for confidence the question was: "How confident were you during the clinical simulation?" The available multiple choice answers were

1. I was not confident at all during the clinical simulation.
2. I was not very confident during the clinical simulation.
3. I was confident during the clinical simulation.
4. I was very confident during the clinical simulation.
5. I was extremely confident during the clinical simulation.

Similar questions with multiple choice answers were asked for the other four affective states.

The self-reports were collected immediately following the clinical part of the evaluation, and before the student nurse watched the video of themselves. This was so that the recollection of their emotion would be freshest in their mind without interrupting the evaluation process.

6.3.3 Pre-processing

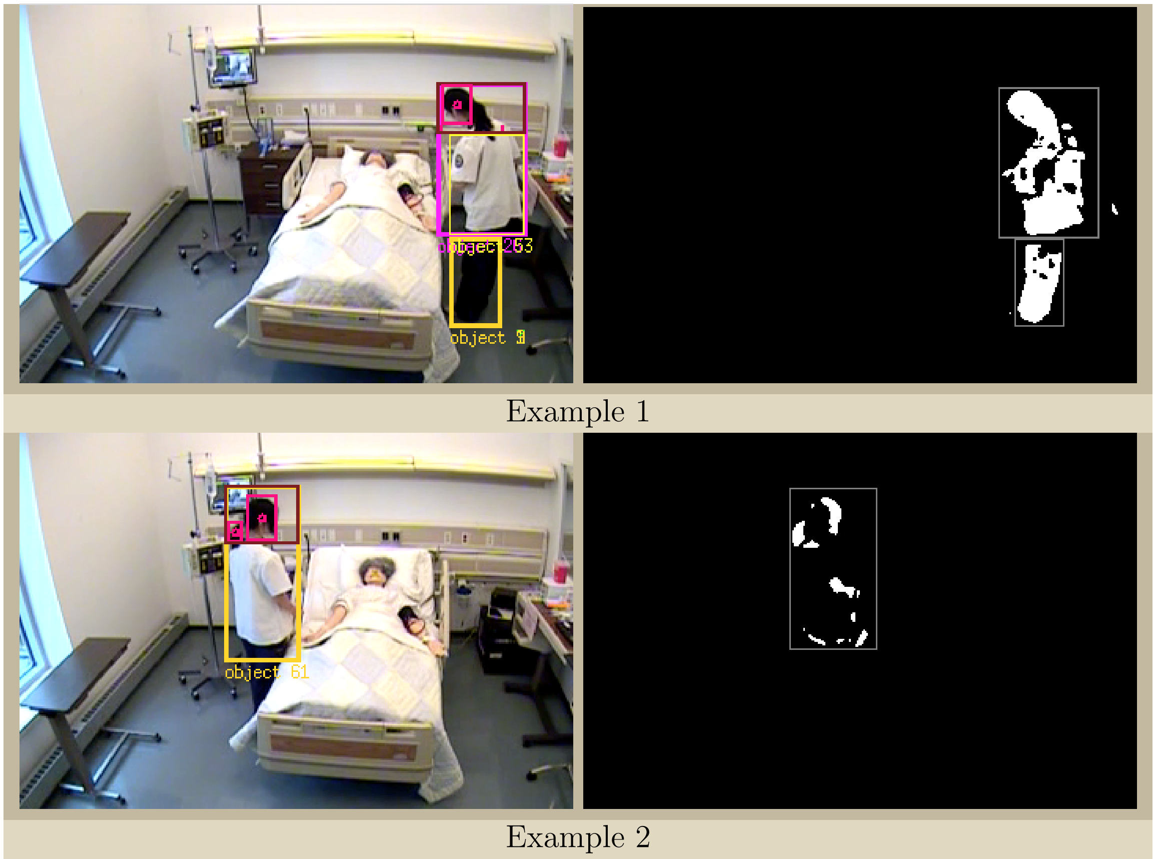
The first step of processing the video is to track the position of the student. Before the above experiment was performed, some preliminary video recordings were taken using a similar setup. These videos were used to determine which tracking algorithm would be used for the study.

6.3.3.1 Person Tracking

The problem of tracking people has been researched in many contexts. Tracking a student nurse in a clinical simulation room is similar to other applications of tracking one person in a room, but there are some key differences. First, the person is much more likely to be facing away from the camera rather than towards it. This is because the camera was positioned to face the simulated patients not the students. Second, the person was typically wearing a white shirt and dark (usually black) pants. Third, much of the room was white or off white in color. In addition, video segments for tracking a person are between ten and thirty minutes in length, and occasionally the person leaves the field of view of the camera.

A number of available implementations of person tracking and detection systems were considered. These include the Reading People Tracker, a pose tracker, the CAMSHIFT tracker, upper body detectors, a Lucas-Kanade feature tracker, and hog based person detection.

Initially, the Reading People Tracker [116] appeared to be a very good choice four this research because it was designed for real time video detection and tracking of people. However, when evaluating the tracker on our data set, the tracker failed to keep track of the nurses, and as many as 200 objects were detected in just the first few minutes of video. Figure 6.2 shows two examples of the tracker on one of the students. The key limitation of the tracker appeared to be that it relied heavily on a motion detection algorithm based on background estimation and subtraction, and when the person stopped for an extended period of time, the track was lost.



Example 1

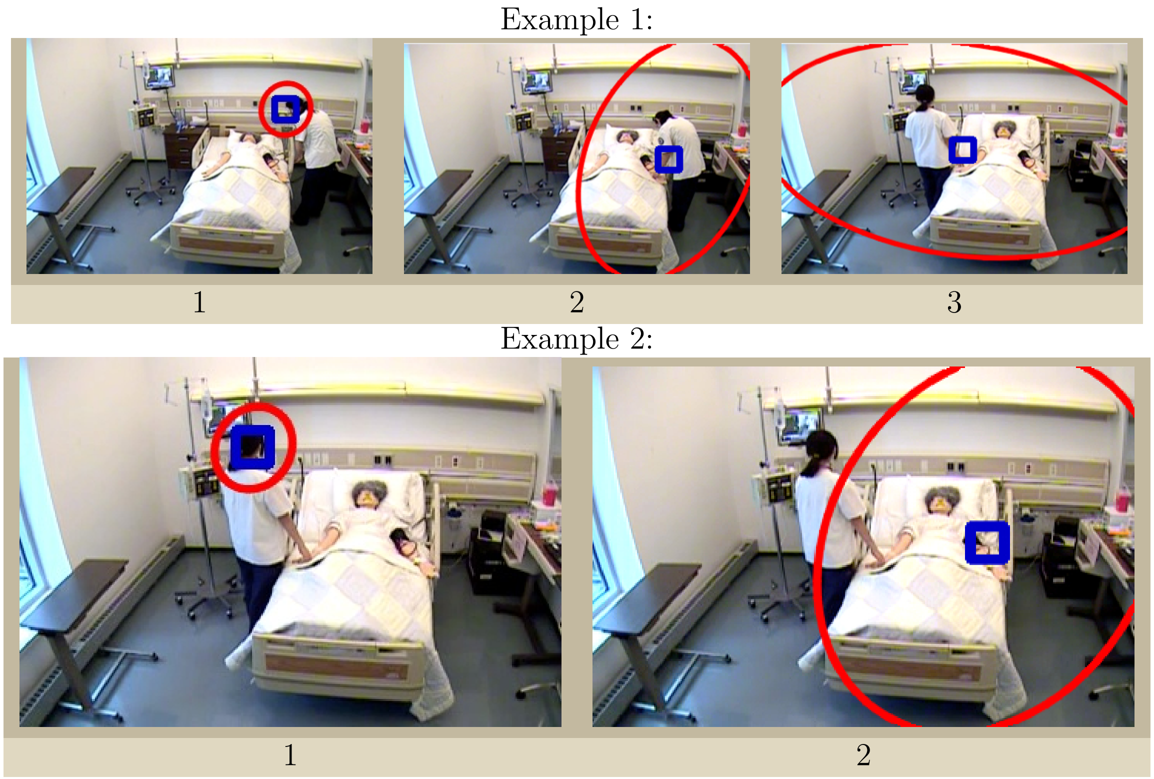
Example 2

Figure 6.2. Two examples of the Reading People Tracker. Yellow rectangles represent objects. Pink rectangles represent upper body. Red rectangles with a small inner rectangle represent heads. top: Multiple objects are found for one person, bottom: the foreground detection of the person begins to fade as the student stands very still.

Ramanan's pose tracker [100, 101] assumes that the torso is approximately 50 pixels in height. When using the model that was included with the demo, the body was in the wrong spot and was the wrong size. When using a new training model, using the same video for training and testing, the tracker did not locate the person at all.

Ferrari's upper body detectors [51] are mainly for forward facing people, and when tested on a sampling of frames there was no a detection.

The CAMSHIFT tracker [18] needs a method for detecting the initial track, and when tested on the whole body, the tracker would quickly enlarge to most of the screen. However, focusing on the head allowed for tracking to last longer, but the size of the track was often wrong. Figure 6.3 shows examples of the CAMSHIFT tracker on one of the students.


Example 1:

Example 2:

Figure 6.3. Two examples of the CAMSHIFT tracker. The blue box is the center of the track, representing the head position. The red ellipse is the area being tracked. top: the tracker center stays near the student, but the size of the track is most of the frame, bottom: the tracker center goes to the wrong side of the patient.

When testing the Lucas-Kanade feature tracker [16], both the body and the head were tried as tracking areas. The body sized tracking performed poorly because the clothing was mostly a solid white or a solid black, so the good points for tracking tended to be the outline of the nurse. This caused the tracking to fail when limbs were moved in different ways and when the nurse's body rotated. The head sized track worked a little bit better, but when the arms were close to the head or when the head went by other objects with similar color, the tracked points would diverge from the head. Figure 6.4 shows an example of the Lucas-Kanade tracker on the head of one of the students from our study.

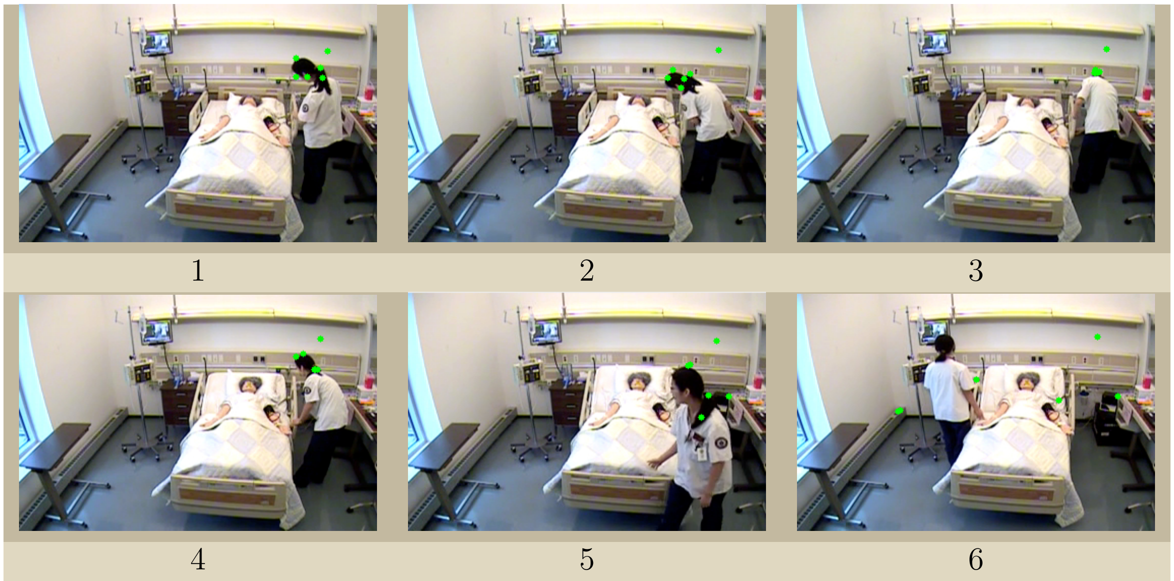


Figure 6.4. An example of the Lucas-Kanade tracker. The head region is selected by hand. As the student moves around the 'good features to track' (in green) disperse away from the head.

The hog based person detection [35] was able to identify the position of a person or part of a person. However, sometimes other parts of the view were also detected as a person. In addition each detection took over 500ms.

In addition to the openly available trackers we also evaluated a generic object tracker based on distribution fields [72]. Like the CAMSHIFT and Lukas-Kanade methods, this tracker does not have an initialization process specific for people. The distribution field (DF) tracker appeared to do a very good job tracking the head of the person. The tracker would keep track for between thirty seconds and five minutes based on visual inspection. Figure 6.5 shows examples of the distribution field tracker with one of the students in our study.

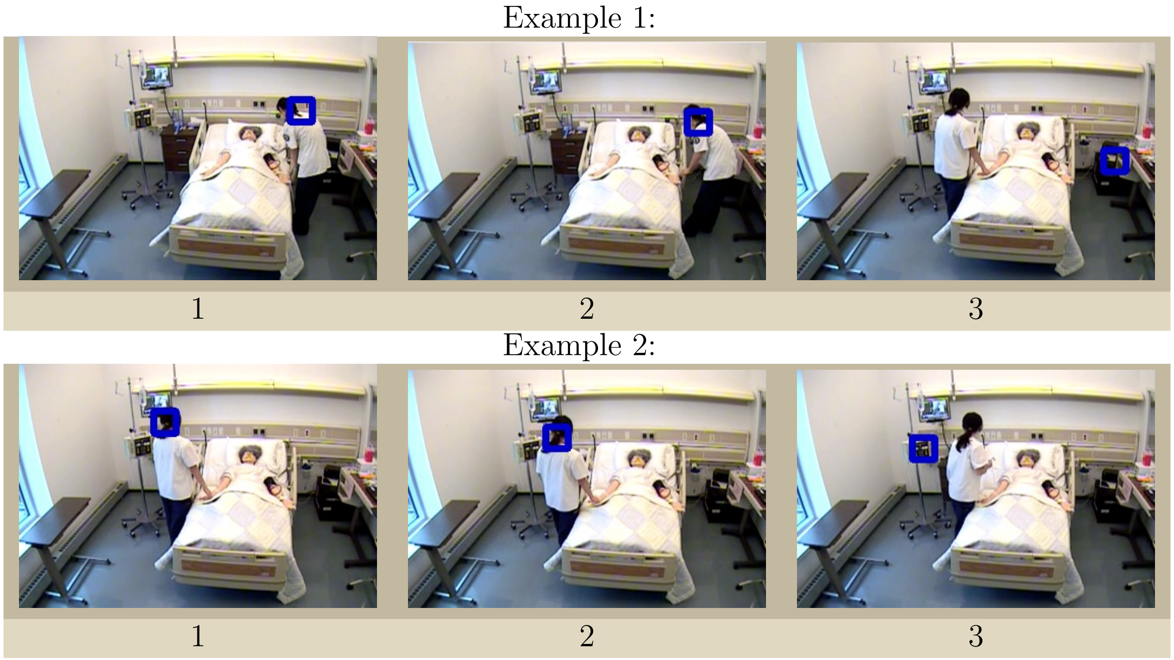


Figure 6.5. Two examples of the distribution field tracker. Blue box represents the area being tracked, in this case, the head of the student. top: tracker incorrectly selects filing cabinet, bottom: tracker incorrectly selects a box with dials

From this early evaluation, it became clear that a method specific for this application would need to be developed. This method is described in Sec. 6.3.3.2.

6.3.3.2 Tracking Algorithm

Ideally, the whole body of a person would be tracked in real time for the full ten to thirty minutes of an evaluation. However, given the available trackers as described in Sec. 6.3.3.1, we started by developing a person tracker that tracked the location of the person's head. The reasons for tracking the head were that 1. the location of the head was likely to be more relevant than other parts of the body when considering emotion, 2. the head had more distinct features than the clothing of the participants, and 3. the head had an image size that was more manageable for computation than the whole body.

The tracker had three stages: 1. initialization, 2. tracking, and 3. recovery. Typically when a head is being detected, either the face is detected using a face detection algorithm, or the head is detected because it is on top of a body. We used an approximation of the latter approach. For initialization we used a background subtraction algorithm to get an estimate of the foreground, and then we used a heuristic that the head was on the part of the highest foreground image that was at least 75% of the size of the track. We set the size of the track to be 40 x 40 on a 640x480 frame, and we scaled the size down proportionally on a smaller frame size. The track was initialized by centering the track at the top of the foreground contour that was selected.

The tracking system was designed such that it can swap in and out different tracking algorithms. For this study we compare four different tracking algorithms with a variety of system parameters. We compare two versions of a distribution field (DF) tracker, the CAMSHIFT tracker, and no tracker (i.e. just continuous initialization).

Recovery was done by first detecting that the track was lost. A lost track is defined as a track that does not overlap at all with any foreground contour that is at least 75% of the head height and width. Once the track is determined to be lost, one or more potential track positions are determined by searching the foreground for contours that are big enough to contain a head, and then the tracker searches for the track from each of those positions, and chooses the best match.

The base algorithm uses the McFarlane and Schofield's background subtraction (BGS) method [81] in order to get an estimate of the foreground. The BGS method was originally intended for tracking piglets and implemented by Parks [93]. This method of background subtraction is based on adaptive median threshold, and, upon visual inspection, it did the best job of creating silhouettes of student nurses while also adapting to the changing position of the patient's bed. The drawback of this method is that when an object or person stops for a prolonged amount of time and then moves again, there is an afterglow or ghost of where the person was standing in addition to the actual foreground silhouette.

Once the foreground is estimated, objects are segregated by the OpenCV [17] implementation of Suzuki and Abe's border following algorithm [122]. For initialization, the system chooses the candidate head as the object with a top closest to the top of the frame, and with a size of at least 75% of the size of a track. If the top of the candidate head is at or above 60% of the height of the frame, then the candidate head position is given to the tracker for initialization. At each time step, the track is compared to the foreground to make sure that the track is not lost. If the track is lost, then the system gives the tracker one or more starting points for regaining the track, and tracking continues.

This algorithm is summarized below in pseudocode.

Algorithm 1: Track Nurse

```
1. head = nil
2. for each frame
   (a) do background subtraction
   (b) get contours
   (c) if no head
           head = initialize track
   (d) else
           lost = track(head)
   (e) if lost
           head = regain
```

The initial implementation of this system used the DF tracker, and did not detect whether the track was lost. It worked well for the first few minutes of one of the videos, but then it would get stuck on a stationary point for a long time and often would never regain the track because the tracker had no way of knowing that the track was lost.

For comparison, the CAMSHIFT tracker from OpenCV was also used for the track and regain steps. Since our algorithm expects the track to remain the same size, the CAMSHIFT tracker is constrained to the initial patch size by centering the patch bounds of the reported track on the CAMSHIFT track regardless of the size of the CAMSHIFT track.

Once the ability to detect a lost track exists, there are a number of ways to regain the track. One is to delete all of the information about the track, then initialize a new track, and another way is to save the model of the track in order to regain the track with the learned appearance model of the track.

In addition, there are other ways that the foreground of the track may be helpful to both the tracker and the BGS method. These are described next.

6.3.3.3 Tracking algorithm variants

6.3.3.3.1 Variant 1a: Foreground distance The DF tracker computes the L_1 distance between the stored model track and the distribution field of the predicted position. One way to augment the tracker is to include a foreground/background model as part of the track so that in addition to comparing the distribution fields, the foreground mask of the predicted position can be compared to the foreground mask model of the track. This modification requires an additional storage of the foreground mask model that is track width by track height in dimension stored as doubles in order to allow the model to be updated over time.

We initialize a foreground mask, fm from the detected foreground, F, in a patch such that

$$fm(i,j) = \begin{cases} 1 & \text{if } F(i,j) = TRUE, \\ 0 & \text{if } F(i,j) = FALSE, \end{cases} \tag{6.1}$$

for all pairs i, j in the image patch where i and j are row and column indices respectively. The foreground masks are compared by the L_1 distance between each other:

$$D_{L1}(fm_1, fm_2) = \sum_{i,j} \left| fm_1(i,j) - fm_2(i,j) \right|. \tag{6.2}$$

When computing the distance between a potential object o and the model m we compute

$$D(m, o) = \frac{1}{p} \left(\alpha D(df_m, df_o) + \beta D(fm_m, fm_o) \right), \tag{6.3}$$

where p is the pixel area of the patch, α and β are mixing parameters. The mixing parameters are necessary to balance the contribution between the distribution field distance and the foreground mask distance. The purpose of using a foreground mask as part of the distance function is so that the shape of the object that is being tracked is modeled in addition to the rectangular patch in which the object appears. This is a loose approximation of fine segmentation as described by Aeschliman et al., [1].

6.3.3.3.2 Variant 1b: Foreground masking For the CAMSHIFT tracker, there is already a mask to remove pixels that are not within a particular hue and saturation range. The foreground prediction can be used as a mask in addition to standard mask, to prevent the CAMSHIFT track from drifting to background that has a similar color model to the head. With this variant, there is just an initial step of taking the intersection of the foreground mask and the CAMSHIFT hue and saturation mask.

6.3.3.3.3 Variant 2: Multiple candidates When tracking, the standard DF tracker predicts the location of the next track based on a motion estimate, and then it searches for the object based on a gradient descent of the distance. The object position is determined by the minimum distance between the model's distribution field and the potential object's distribution field.

By using the foreground contours, in addition to the predicted object's position as a candidate for gradient descent, other candidates are selected by finding potential heads (i.e. contours that are at least 75% of the track size), and extracting a patch that is centered at the top of the contour. Then the multiple candidates are used for the gradient descent search, and the basin with the lowest distance will be the tracked position.

By having multiple candidates, the tracker may be able to recover from quick changes in velocity.

6.3.3.3.4 Variant 3: Track based conditional background updates By default, when the BGS algorithm updates its background model, the entire frame is used to update the model. However, there is the option to pass in a foreground mask that will not update the model. This variant of our tracker selects every foreground contour that the track overlaps with, and adds these contours to the foreground mask that is passed to the BGS algorithm. If the track is tracking correctly, then this should remove the ghosting problems that occur when a person stays in one place for a long time.

6.3.3.3.5 Variant 4: Re-initialize instead of regain tracks en a track is lost, there is a potential that the model for the track has been corrupted due to misalignment with the track. If this is the case, then the process of regaining the track could potentially choose the wrong candidate head. One way to mitigate this problem is to re-initialize the track based on the initialization heuristic. The pro for this approach is that the model does not have corrupted data. The con is that the initialization could choose the wrong position, and then the model would not just be corrupted, but would be altogether bad. Though, this variant may not be an ideal solution, it is very easy to implement and compare.

6.3.4 Tracking Comparison

In order to evaluate the tracking, the head position of the students were labeled every 30 seconds. If the student was off of the screen then the label was marked as such because it was out of the frame, and the label was not used. This yielded 2027 labels total, and an average of 38 labels per video. Using this data, the trackers were compared based on the distance to the labeled tracks. 24 variants of the DF tracker, 16 variants of the CAMSHIFT tracker, and four variants of initialization only were compared. The best ten trackers were then used to find the best features for affect classification.

6.3.5 Tracking Results

Figure 6.6 shows a box plot of the distances from the labeled ground truth for all labels over all of the students for the top ten trackers. It appears from this box plot, that the top three trackers are those that use no tracking at all, rather they initialize (steps 1 and 2 a-c of Algorithm 1) the track at each time step. However, there are many outliers in all of the tracking results, so there is much room for improvement in tracking. In addition, since samples are only every thirty seconds we have no quantitative evaluation of the velocity accuracy of the tracking.

6.3.6 Video Events

Once the video is preprocessed with tracking information about the head of the nurse, the location of the track can be further processed into video events relating to the interactions in the room. These interactions are defined by key locations in the room that correspond to points of interaction. There are two sets of key points. The first set is for the room with only one patient, and the key points are the head of the patient, the center of the monitor, and the location of the phone. The second set is for the room with two patients, so there is a point for the head of each patient, and one for the phone. Since the monitor is between the two patients, but closer to one

Tracker	μ Dist.
nc	37.06
ncfg	40.07
ncg	40.32
ic	49.99
isc	51.01
isct	56.85
ncf	57.31
ict	59.13
abic	59.66
aic	59.73

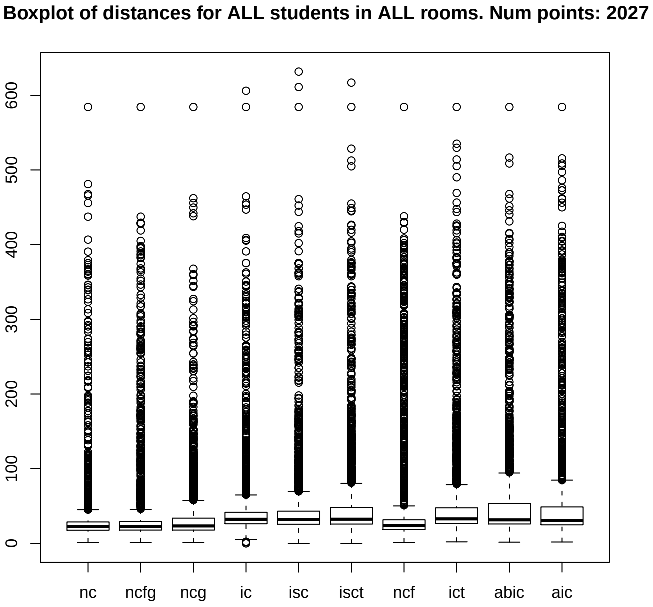


Figure 6.6. Left: Top ten trackers in order of increasing mean squared error. Right: Box plot of distances from ground truth for top ten trackers. Trackers beginning with ‘n’ use only initialization, trackers beginning with ‘a’ are variants of the CAMSHIFT tracker, and trackers beginning with ‘i’ are the DF trackers.

patient than the other, the monitor was not included as a key point for the second set because it could get confused with interaction with the patient closest to the monitor.

There were six potential room configurations: Three room configurations for each set. In one configuration, the student enters on the left side, the phone is at the left wall of the room, the patient is in the center of the room, and the monitor is on the right side of the patient from the camera’s point of view. The next configuration is the mirror image of the first, where the student nurse enters on the right side of the room, the telephone is on the right wall, and the monitor is on the left side of the patient with respect to the camera. In the third set, the video is compressed, and the phone is out of view, but it is basically the same as the second set otherwise: The student enters from the right, the patient is in the center of the room, and the monitor is on the left side of the patient with respect to the video camera. The final three room sets are identical to the first three except that there is an additional patient next to the far wall.

Using the three key points in the room, the tracking information about the head location is used to find the approximate distance from the head of the student nurse to each key point ten times per second. From this data, the distances are binned such that at each time, the closest distance is binned to the closest key point. Figure 6.7 shows two examples of the binned predicted head positions. From this, three bins are created for each student, and basic statistics (mean, min, max, and std. dev.) of the distances are taken about each bin. In addition, the size of each bin, and the number of switches to another bin are computed.

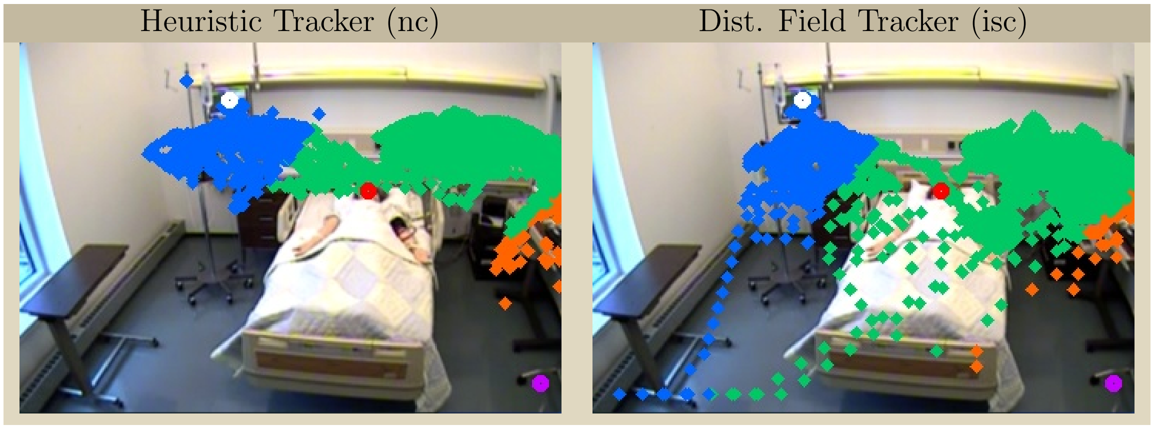


Figure 6.7. The predicted head positions of one student for two different trackers. Blue points predict closest to monitor. Green points predict closest to patient, and Orange points predict student closest to the telephone. Left: heuristic detection (no tracking). Right: distribution field tracker

This leaves us with 18 features, six for each location. The min, mean, and max distance as well as the amount of time near the location has to do with proximity which loosely corresponds to the acceptance and rejection axis of the Personal Interaction Coding Inventory (PICI) [15], and the std. deviation of the distance and the number of switches, loosely corresponds to the levels of activity axis of the PICI.

6.3.6.1 Feature Selection

From the tracking data we collect distance information from three key points in the room, and then create 6 features related to each key point for a total of 18 features as described in Section 6.3.1. We then do branch and bound search using linear regression to select at most 8 of the 18 available features. We do a leave one out cross-validation on the R^2 values as well as on classifiers that result from the linear regression. Table 6.1 summarizes the cross-validated mean R^2 values for the five best trackers based on the mean distance from ground truth. Note that of the five trackers shown, the nc tracker, which is the most basic tracker, has most of the best mean R^2 values. However, when looking at the best classifier results some of the bottom five of the top ten performed better with a particular group on a particular emotion. Most notably, the ncf tracker, shown in Figure 6.6 and Table 6.2, which utilizes tracking algorithm Variant 3.

Table 6.1. Cross-validated mean R^2 values for the five best trackers. Each cell corresponds to a linear model to predict emotion self-reports. Models were generated using a branch and bound linear regression. The top row lists the tracker. The left column lists the emotional self-reports being predicted and the group that reports are predicted for. R^2 values correspond to the fit of the model (best fit models for each emotion are in **bold**). Group A had one simulated patient and Group B had two simulated patients. Each group has 23 students reporting emotions.

Tracker	nc	ncfg	ncg	ic	isc
Confident A	0.80	0.77	**0.87**	0.76	0.76
B	**0.88**	0.68	0.77	**0.88**	0.80
Anxious A	0.73	**0.85**	0.79	0.66	0.68
B	**0.80**	**0.80**	0.75	0.77	**0.80**
Frustrated A	**0.81**	0.72	0.78	0.80	0.65
B	**0.78**	**0.78**	0.73	0.76	0.70
Excited A	0.69	0.74	0.62	**0.81**	**0.81**
B	**0.86**	0.68	0.73	0.75	0.70
Interested A	**0.85**	0.63	0.73	0.62	0.84
B	**0.88**	0.82	0.84	0.84	0.81

Table 6.2 shows results for the best accuracy classifiers. Note that the many of the best classifiers do not come from the top five trackers. This is not surprising

Emotion	Common feature(s) between groups A and B
Confident	minimum distance to phone
Anxious	motion near patient & switches from phone
Frustrated	number of switches from phone
Excited	maximum distance from patient
Interested	time near patient

Figure 6.8. The PICI features that are common between groups A and B.

since the top ten classifiers have a large variance in their distances to ground truth. The features that are used for both Group A and Group B of the best classifiers for a student's emotion of *anxious* are the motion while near the patient's head, and the number of switches from the phone. For *confident*, the feature in common is the minimum distance to the phone. For *frustration*, the feature in common is the number of phone switches. For *interested*, time near the patient is in common. For *excited*, the maximum distance from the patient is in common as a feature. These common features are summarized in Figure 6.8.

Table 6.2. The ten best classifiers, one for each emotion for each group. Trackers starting with an i are DF trackers using variant 4. f indicates using variant 3. g indicates using variant 5. a indicates the CAMSHIFT tracker, and b indicates using variant 1b. t indicates using variant 1a. s indicates using the faster variant of the DF tracker, and n indicates that just initialization is done.

Emotion	R^2	Accuracy	Baseline	Difference	Tracker
Confident A	0.90	0.78	0.56	*0.22*	ict
B	0.88	0.87	0.78	*0.09*	**nc**
Anxious A	0.85	0.87	0.61	*0.26*	**ncfg**
B	0.77	0.70	0.56	*0.14*	**ic**
Frustrated A	0.82	0.78	0.61	*0.17*	ncf
B	0.92	0.91	0.70	*0.21*	ncf
Excited A	0.81	0.70	0.61	*0.09*	**ic**
B	0.78	0.56	0.65	-0.09	isct
Interested A	0.86	0.78	0.61	*0.17*	abic
B	0.83	0.78	0.52	*0.26*	ict

6.4 Voice Features

Before we can collect voice features of the student, we need a method to first differentiate between the voices of the student and the instructor, and second to identify and keep track of the students utterances. The former is known as speaker segmentation, and the latter is known as speaker tracking. There are a number of methods for speaker segmentation [71, 85, 99, 75, 21, 134, 76, 103]. Lu et al.'s, method [76] for speaker segmentation uses a line spectral pair (LSP) coding as features for an iterative pseudo Gaussian mixture model (GMM) that detects speaker changes by the Bayesian information criterion (BIC). This speaker segmentation model was implemented in the open source framework MARSYAS by Martins [71]. Kotti et al., use the F_1 measure defined as

$$F_1 = \frac{2 * Precision * Recall}{Precision + Recall}. \tag{6.4}$$

This method for speaker segregation has an F_1 measure of 0.8666 for a set of news data [76], and 0.730 using the TIMIT data base [71].

Given the performance and availability of this method, we used the method on one 10 minute speech segment from the participants of our study. We then checked the resulting detections by listening to a few seconds of the audio before and after a detection. We found that rather than detecting when the student and the instructor switched, the detector was often detecting when the student changed her tone of voice, or there was a change from a long silence to someone speaking.

We then modified the speaker segregation algorithm to also use Mel frequency cepstrum coefficients (MFCC), since Kotti et al., suggested that MFCC may be useful for speaker segmentation [70]. This modification showed very little qualitative differences in performance.

Since we were unable to adequately separate the student's speech from the instructor's we did not do further analysis of the voice signal of the student nurses related to their self-reported emotions. Though the majority of the speech is the student nurse's, it is unclear at this time how much the features would be corrupted by the instructor's voice.

6.4.1 Future work

There are a number of directions that the voice analysis could go. Ideally an automatic method can be created for separating the student's speech from the instructor's speech. Without that, the speech data could be extracted by a human. Once the data is separated, then the methods described in Section 5.3 could be used on the emotional labels used for the video classification in Section 6.3.2. In addition, extracting audio events based on extracted video events such as close proximity to a patient, may be a very effective method of finding salient affective features.

6.5 Discussion & Future Work

Detecting the emotions of people as they interact with their environment has many potential applications. This study indicates that simple motion cues relative to key interaction points may be enough to computationally assess the affective state of a person. This study also identifies some limitations of current real-time trackers. There is a lot of room for improvement so that a tracker can track the head more closely, and recover better from when the location of the head is lost.

In addition, the potential exists to use the time series of the data rather than just basic statistics over the entire session. Once tracking is better, it would be interesting to see if more gestural information could be captured from the foreground contours. This may require much higher fidelity labeling of the data.

Labeling the head position every half minute allowed us to validate how well the trackers were doing at various check points, but labeling every half second (or even every frame) would be preferred. This would be an ideal application for crowd sourcing, however, it would be difficult to keep the privacy of the participants.

One place for future work is to run a follow-up study with multiple schools of nursing that have a similar setup. This way we can recruit a larger participant pool to verify our results.

CHAPTER 7
DISCUSSION AND FUTURE WORK

7.1 Hypotheses Revisited

1. Sensors can effectively augment tutor logs in order to predict the self-reported emotions of students.

   True. The linear least square regression results from Chapter 3 indicate that sensors do indeed improve the prediction quality of self-reported emotions for all four of the emotions in question confident, frustrated, excited, and interested, as shown in Table 3.3.

2. Linear least squares classifiers built from the tutor and sensor data can predict high vs. low levels of frustration, confidence, interest, and excitement.

   Mixed. This hypothesis held true for confident, excited, and interested, but it was false for frustrated. We were unable to use a linear least squares classifier for frustrated that was significantly better than using no classifier at all.

3. The accuracy, specificity, and/or sensitivity of the frustration, confidence, interest, and excitement classifiers that use tutor and/or sensor features will continue to perform significantly better than the baseline classifier for the given emotion on a novel population.

   Mixed. This held true for specificity results for confidence. It also held true for sensitivity results for interest and excitement. However, overall accuracy was not held up for any of the four emotions.

4. The method of feature selection and linear least squares classification will transfer to the voice domain.

   Mixed For the two class problems, such as gender and American vs. Asian voices, the method shows better than baseline performance, however, the method appears to be insufficient for the multi-class problem of multiple cultures in voice.

5. Low confidence is correlated with high anxiety in learning situations.

   True. When comparing levels of self-reported confidence and anxiety about the student's test in the health care education experiment, the correlation test showed a high negative correlation using Pearson's product moment correlation test: $r = -0.632$, $t = -5.48$, $df = 45$, p-value$= 9.235e - 07$, with a 95% confidence interval of [-1.0,-0.46]. This is strong evidence that there is a high correlation between low confidence and high anxiety in learning situations.

6. Available methods for real-time people tracking are adequate for tracking the nurses in the video.

   Mixed. When looking at the results of the tracker comparison in Figure 6.6, there are clearly a lot of outliers for all of the trackers. This suggests that there are many cases where the tracker is not correctly tracking the position of the head of the student. However, the features gleaned from the tracking predictions were good enough to make classifiers that performed better than chance.

7. PICI related features in the video will help to predict or classify the self-reported emotional state of the student.

True. We were able to find both motion and proximity related features that helped classify low and high levels of all five of the emotional states in question (anxious, confident, excited, frustrated, and interested). Classifier results of best classifiers are summarized in Table 6.2.

8. Contemporary methods for automatic extraction of audio will be sufficient to separate the student nurses voice from other sounds and voices in the audio recording.

   False. The available method for speaker segregation is not good enough to extract the students voice from the other voices and sounds in the recording.

9. Prosodic features will be relevant for emotional change.

   Unknown. We could not explore this hypothesis adequately given the nature of the audio data. Either an automatic speaker segregation algorithm or hand extraction is needed for this to be tested.

7.2 Lessons Learned and Future Directions

7.2.1 Computer Based Education

7.2.1.1 Sensors

The use of over 100 sensors at a time is a very ambitious endeavor. The research in Chapters 3 and 4 is just the first step in determining the usefulness of these sensors for detecting affect in ITS settings. The sensor values that ended up performing well were those that correlated most with a particular action of the student rather than the raw sensor values. With that in mind, one next step for future directions may be using an automatic feature discovery algorithm based on the temporal data. This could be using time series motif discovery, topic models, hidden Markov models (HMM), or deep belief networks. We began looking at time series motif discovery for just the tutor data with some promising results [112], but we have yet to look at the sensor data in that way. We did a preliminary exploration of topic models using the sensor and tutor data together, however the topics found did not yield good classifiers, and it was unclear whether we translated the data to documents in the best way. Further exploration will have to be done before topic modeling should be ruled out.

7.2.1.2 Controls

If we were to run more studies with the sensors in the future, it would be useful to collect some baseline data with the sensors when the students are doing a sequence of known activities without problem solving. In this way we can have an idea of the way that students differ from the norm with a fixed set of activities that can be compared in a more controlled way. Since we only had data from a hard to control environment, it was difficult to determine the amount of noise or spurious data there was with the affective signal.

7.2.1.3 Feedback

Now that we have some idea of how the students are feeling, the next step is to target our emotional queries so that we can ask about a feeling that is likely to occur. For instance, if the system detects that the student is anxious, then the question "How confident are you feeling?" would be displayed to the student. This way we can improve our classifiers with more relevant data.

7.2.2 Speaker Differences and Health Diagnosis

7.2.2.1 Classifiers

Our research found that for the multi-class problem of differentiating four cultures, the linear least squares classifier was insufficient. There are a number of other methods that may work better for this. Linear models such as linear discriminant analysis (LDA) and logistic regression classifiers are one option. Another option is to use a k-nearest neighbors technique, which allows for local linear relationships. Support

Vector Machines (SVM) can use polynomial or radial basis kernels which may work better for multi-class problems as well.

7.2.2.2 Categories

In addition to the categories of gender and culture. Using similar computational methods for categorizing different health conditions such as differentiating typically developing (TD) children from childhood apraxia of speech (CAS) and autism spectrum disorder (ASD) is the logical next step for this work. In addition, directly evaluating speech from evoked emotions is an important next step.

7.2.3 Heath Care Education

The student nurse pilot study was a very good first step for collecting a data set for understanding emotion from video and voice. However, there is potential to increase the quality of future data collection efforts.

7.2.3.1 Controls

One aspect that can be improved is the creation of controlled interaction with the key points in the room. This could be done by creating a control scenario in the simulation room with tasks that just involve moving around the room and speaking, without having to evaluate a patient or talk to a doctor over the phone. By having each participant enact a script that has little or no emotional charge to it, the participants can be compared to themselves in the control condition to determine how emotional they are being.

There are other controls that were considered, but are both infeasible and undesirable in order to maintain ecological validity. These are having a microphone a fixed distance from the participant at all times, controlling for ambient noise and other noise sources, and limiting speech to one speaker at a time. Rather than control for these, there is a need for new methods to handle these conditions that exist in this test environment as well as other environments where a single fixed camera and microphone are in the room.

7.2.3.2 Self-Reports

In order to make binary classifiers, the self reports that are on a 1-5 scale had to be split at a threshold. Since many of the self-reported values fell exactly in the middle, the threshold was determined by which direction balanced the data more. In the future, having either a four or six point scale would be preferred so that classification ambiguity is not inherent in the labels.

7.2.3.3 Other Judges

In addition to having self-reported emotion, it may be useful to have other judges of the emotional state of the student. One obvious judge would be the proctor(s) of the test, however, since they are busy evaluating the student as they are running the simulation, there is no real time to do this during the evaluation, and the proctors generally are not available immediately after the evaluation, since they are evaluating the next student.

7.3 Summary

The work presented in this dissertation is an early step to applying computational methods to affect detection in education and health care. As sensors continue to be more prevalent and pervasive in our society, we will be more able to utilize them for affect detection in order for computers to better assist and interact with people. Some potential future applications of this work are the creation of a smart home for independent living of the elderly where the occupant is observed by a computational assistant. The detected emotions could help determine which people and activities give the occupant positive affect. In addition a system like that may be able to help identify when someone is trying to take advantage of the occupant and notify a friend, and/or the occupant. For education, there could be virtual assistants for the overloaded teachers that are both identifying affective difficulty and helping students by offering other activities or approaches to the problem. Much work still needs to be done in order to have pervasive affective sensing, but this work brings us one step closer.

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