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# Affectively intelligent and adaptive car interfaces

Fatma Nasoz [a], Christine L. Lisetti [b], Athanasios V. Vasilakos [c,*]

[a] School of Informatics, University of Nevada, Las Vegas, NV 89154, United States
[b] School of Computing and Information Sciences, Florida International University, Miami, FL 33199, United States
[c] Department of Computer and Telecommunications Engineering, University of Western Macedonia, 50100 Kozani, Greece

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ABSTRACT

In this article, we describe a new approach to enhance driving safety via multi-media technologies by recognizing and adapting to drivers' emotions with multi-modal intelligent car interfaces. The primary objective of this research was to build an *affectively intelligent* and *adaptive car interface* that could facilitate a natural communication with its user (i.e., the driver). This objective was achieved by recognizing drivers' affective states (i.e., emotions experienced by the drivers) and by responding to those emotions by adapting to the current situation via an affective user model created for each individual driver. A controlled experiment was designed and conducted in a virtual reality environment to collect physiological data signals (galvanic skin response, heart rate, and temperature) from participants who experienced driving-related emotions and states (neutrality, panic/fear, frustration/anger, and boredom/sleepiness). *k*-Nearest Neighbor (KNN), Marquardt-Backpropagation (MBP), and Resilient Backpropagation (RBP) Algorithms were implemented to analyze the collected data signals and to find unique physiological patterns of emotions. RBP was the best classifier of these three emotions with 82.6% accuracy, followed by MBP with 73.26% and by KNN with 65.33%. Adaptation of the interface was designed to provide multi-modal feedback to the users about their current affective state and to respond to users' negative emotional states in order to decrease the possible negative impacts of those emotions. Bayesian Belief Networks formalization was employed to develop the user model to enable the intelligent system to appropriately adapt to the current context and situation by considering user-dependent factors, such as personality traits and preferences.
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## 1. Introduction and motivation

In recent years there have been increasing attempts to develop computer systems and interfaces that recognize their users' affective states, learn their preferences and personality, and adapt to these distinctions accordingly [1,5,27,30,33,38,43,45,46].

The main motivation behind many of these studies is that humans are social beings that emote and are affected by their emotions. Machine perception needs to be able to capture this experience in order to enhance everyday digital tools. Previous studies suggest that people emote while performing various everyday tasks. For example, people emote while interacting with computers [40] and automobile drivers emote while driving [23]. The important question is whether this is reason enough to justify the creation of Affective Interfaces with an Intelligent Agent that recognize user's emotional states and respond accordingly.

* Corresponding author.
*E-mail addresses:* fatma.nasoz@unlv.edu (F. Nasoz), lisetti@cis.fiu.edu (C.L. Lisetti), vasilako@ath.forthnet.gr (A.V. Vasilakos).

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People do not only emote, but they also are affected by their emotional states. Emotions influence various cognitive processes of people including: perception and organization of memory [7], categorization and preference [49], goal generation, evaluation, and decision-making [13], strategic planning [26], focus and attention[14], motivation and performance [11], intention [16], communication [6], and learning [18]. The strong interface between emotion and cognition and the effects of emotion on human performance in everyday tasks make it necessary to create intelligent computer systems that understand users' emotional states, learn their preferences and personality, and respond accordingly.

A common everyday task is driving, and yet research suggests that people emote while driving and their driving is affected by their emotions [23]. The inability to control one's emotions while driving is often identified as one of the major causes for accidents. Anger is one of the emotions that negatively affects driving. When drivers become angry, they start feeling self-righteous about events and anger impairs their normal thinking and judgment, as a result their perception is altered, which leads to the misinterpretation of events [23]. Fatigue and sleepiness are other very dangerous states to be in while driving. According to National Highway Traffic Safety Administration (NHTSA) drowsy driving is responsible for approximately 56,000 automobile crashes every year. The result of these crashes is roughly 40,000 nonfatal injuries and 1550 fatalities annually. Other states that lead to negative effects while driving are frustration, anxiety, fear, and stress [17].

To be a safer driver on the highways, a person needs to be better aware of his emotions and possess the ability to control them effectively [23]. For some drivers, once they are aware of their emotional states it becomes easier for them to respond to the situation in a safe manner and some drivers often lack the ability to calm themselves down even when they are aware of the fact that they are angry or frustrated [23].

James and Nahl [23] and Larson and Rodriguez [25] discussed techniques for drivers to manage their anger including relaxation techniques to reduce physical arousal and mental reappraisal of the situation. Our aim in creating an affective intelligent car interface is to enhance driving safety by facilitating a natural human–computer interaction with the driver and help the driver to be better aware of his emotional state while driving. For example, when the intelligent system recognizes the anger or rage of a driver it might suggest the driver to perform a breathing exercise [25]. Similarly, when the system recognizes driver's sleepiness, it might change the radio station for a different tune or roll down the window for fresh air. Taking the precautions mentioned above automatically without distracting the driver through an affectively intelligent and adaptive system will enhance the driving safety.

Fig. 1, which was originally developed and introduced by Lisetti [28], shows the overall architecture of the system that would recognize the driver's current affective state and respond accordingly [5]. This architecture is the backbone of an intelligent adaptive computer system called Multimodal Affective User Interface (MAUI) [29] that can recognize user emotions and adapt to them by considering user-dependent factors such as personality traits and preferences. The affective state of

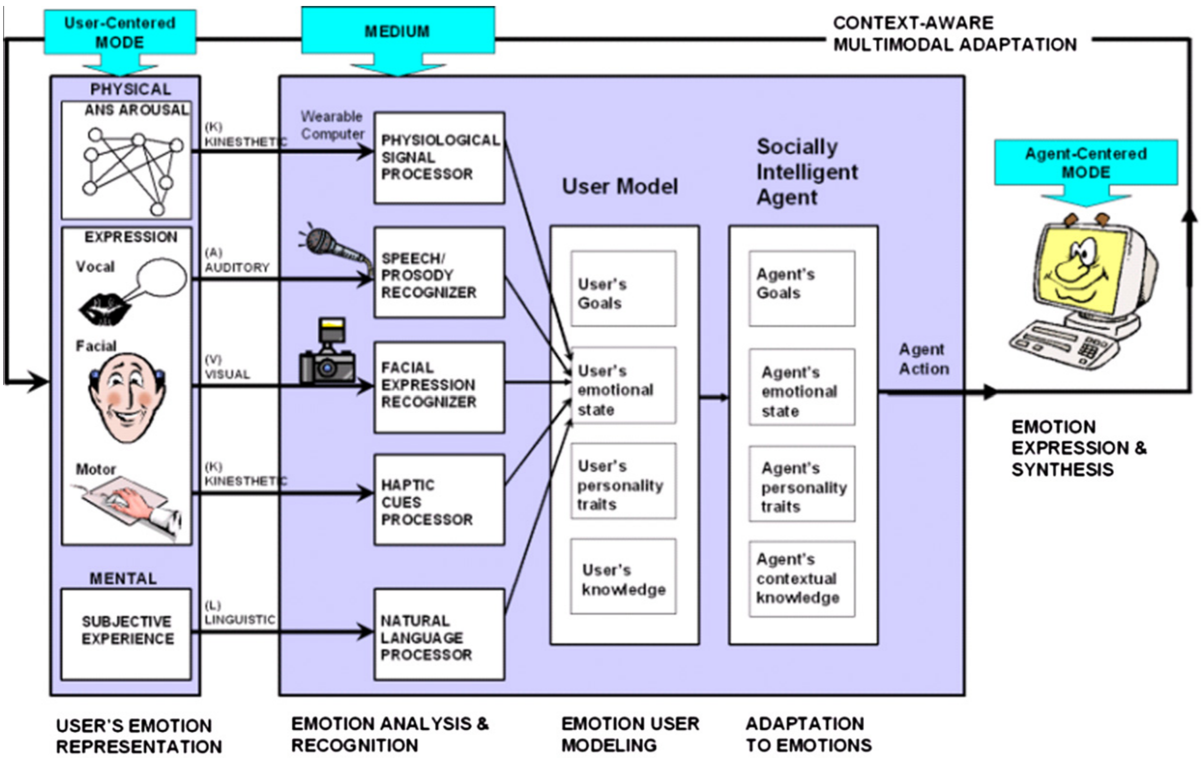


**Fig. 1.** Human multi-modal affect expression matched with multi-media computer sensing.

a driver can be assessed by interpreting both the mental and the physiological components of the particular emotion experienced by the driver. Physiological components can be identified and collected from observing the driver using sensors with different modalities: Visual (facial expressions), Kinesthetic (autonomic nervous system [ANS] arousal and motor activities), and Auditory (vocal intonation) (V, K, A).

The input is interpreted by implementing various pattern recognition algorithms such as Artificial Neural Networks. The output of the system is given in the form of a synthesis for the most likely emotion concept corresponding to the sensory observations. This synthesis constitutes a descriptive feedback to the user about her current emotional state and includes suggestions as to what action might be taken next to change that emotional state.

This research focused on recognizing the affective states of drivers by collecting physiological signals and analyzing those signals with machine learning algorithms, and adapting to these affective states through user modeling. We designed and conducted a driving simulator experiment in virtual reality as discussed in Section 4. In this experiment various scenarios were created to elicit driving-related emotions and states (neutrality, panic/fear, frustration/anger, and boredom/fatigue) from the participants. In order to effectively elicit the targeted emotions the scenarios duplicated problematic situations in real-life driving.

Before designing the driving simulator experiment in virtual reality we studied previous research that performed emotion recognition through analysis and interpretation of physiological signals. We designed and conducted preliminary experiments to find a relationship between certain physiological signals and emotions. The following section presents previous studies on emotion recognition through physiology.

## 2. Related research

This section presents information on research studying the relationship between physiology and emotions and a study that was specifically focused on assessing level of drivers' stress.

### *2.1. Emotion recognition from physiological signals*

There have been several studies conducted on understanding the connection between emotions and physiological arousal. Manual analyses (i.e., where no statistical analyses or computer algorithm method was employed) have been successfully used for this purpose [15,20]. However, interpreting the data with statistical methods and algorithms is beneficial in terms of actually being able to map them to specific emotions. Studies have demonstrated that algorithms can be successfully implemented for recognition of emotions from physiological signals [39,48,50].

Picard et al. [39] used pictures and guided imagery techniques (i.e., where participants are instructed to imagine experiencing an emotionally loaded event) to elicit happiness, sadness, anger, fear, disgust, surprise, neutrality, platonic love, and romantic love. The physiological signals measured were electromyogram, blood volume pressure, skin conductance, and respiration. The algorithms used to analyze the data were Sequential Forward Floating Selection (SFFS), Fisher Projection, and a hybrid of these two. The best classification achievement was gained by the hybrid method, which resulted in 81% overall accuracy in mapping the physiological signals into eight emotion groups.

In Zhai and Barreto's [50] research participants played a computer game where they encountered stress due to the nature of the game, while their blood volume pressure, galvanic skin response, pupil diameter, and skin temperature were collected with a non-invasive biofeedback system. By employing Support Vector Machine learning algorithms to analyze the collected data the researchers categorized different levels of stress with 90.1% accuracy.

In Westerink et al.'s [48] study participants watched emotionally loaded movie clips while their physiological signals were measured. The study focused on recognizing participants' affective states through six parameters (i.e., mean, absolute deviation, standard deviation, variance, skewness, and kurtosis) of galvanic skin response (GSR) and of three electromyography signals: frontalis, corrugator supercilii, and zygomaticus major. The skewness and kurtosis parameters of GSR, the skewness of corrugator supercilii, and four parameters of zygomaticus major successfully discriminated among the four emotion categories of negative, positive, mixed, and neutral.

All this previous research is aimed to accurately measure users' physiological signals and classify them into affective states, so that the technology can be integrated with the development of various user interfaces to facilitate a more natural interaction between computers and their users.

### *2.2. A previous study on measuring drivers' stress*

Jennifer Healey's research from Massachusetts Institute of Technology (MIT) Media Lab [22] was focused on recognizing stress levels of drivers by measuring and analyzing their physiological signals. The study answered the questions about how affective models of users should be developed for computer systems and how computers should respond to the emotional states of users appropriately. The results showed that people don't just create preference lists, but they use affective expression to communicate and to show their satisfaction or dissatisfaction.

Before Healey's driving experiment was conducted a preliminary emotion elicitation experiment was designed where eight states (anger, hate, grief, love, romantic love, joy, reverence, and no emotion i.e. neutrality) were elicited from the participants. These eight emotions were Clynes' [10] original set for basic emotions. This set of emotions was chosen to be elicited in the experiment because each was found to produce a unique set of finger pressure patterns [10]. While the participants were experiencing these emotions the changes in their physiological responses were measured. The sensors used to measure various physiological signals are shown in Table 1.

The experiment was conducted over 32 days in a single subject-multiple session setup resulting in 32 different experiments. However only twenty sets (days) of complete data were obtained at the end of the experiment. Guided imagery technique (i.e., the participant imagines that she is experiencing the emotion by picturing herself in a certain given scenario) was used to generate the emotions listed above. The participant attempted to feel and express eight emotions for a varying period of 3–5 min (with random variations). At the end of the experiment, the participant reported the arousal level and the valence (i.e., positive vs. negative) of each emotion she experienced, which is summarized in Table 2.

Eleven features were extracted from raw electromyogram (EMG), skin conductance (SC), blood volume pulse (BVP) and respiration measurements by calculating the mean, the normalized mean, the normalized first difference mean, and the first forward distance mean of the physiological signals. Eleven dimensional feature space of 160 emotions was projected into a two dimensional space by using Fisher projection. Leave-one-out cross validation (i.e., where a single instance from the original data is used for validation and the remaining instances are used for training) was used for emotion classification. The results showed that it was hard to discriminate all eight emotion states. However when the emotions were grouped as being (1) anger or peaceful, (2) high arousal or low arousal, and (3) positive valence or negative valence, they could be classified successfully as follows:

- Anger: 100%, Peaceful: 98%.
- High arousal: 80%, Low arousal: 88%.
- Positive: 82%, Negative: 50%.

Another preliminary experiment was the daily monitoring of a participant while she was performing normal activities. The goal was to determine how feasible the ambulatory (i.e., not stationary; movable) affect detection would be. EMG, BVP, respiration, and SC sensors were used to measure physiological signals while the participant performed her daily activities and made annotation at certain times.

The anecdotal results showed that emotion recognition is hard in ambulatory environments because of the motion artifacts and difficulty of capturing and coding physical and emotional events. For example EMG indicated more muscle activity in the morning than later in the day. It might be due to an emotional episode, but it was most likely due to a motor activity where the participant carried the wearable computer on the left shoulder in the morning and then carried it on her lap later in the day. These findings influenced the design of the final driving experiment.

The results of the experiments described above showed that it is difficult to perform emotion recognition during natural situations. So, the scope of Healey's driving experiment was limited to recognition of levels of only one emotional state, which was emotional stress.

The experiment had three stages: driving in and exiting a parking garage; driving in a city; and driving on a highway. The experiment used three subjects who repeated the experiment multiple times and six subjects who drove only once. Videos of the participants were recorded during the experiments and self-reports were obtained at the end of each session. Task design and questionnaire responses were used to recognize the driver's stress separately. The results obtained from these two methods were as follows:

- Task design analysis recognized driver stress level as being rest (e.g. resting in the parking garage), city (e.g. driving in Boston streets), or highway (e.g. two lane merge on the highway) with 96% accuracy.
- Questionnaire analysis categorized four stress classes as being lowest, low, higher, or highest with 88.6% accuracy.

Finally, video recordings were annotated on a second by second basis by two independent researchers for validation purposes. This annotation was used to find a correlation between the stress metric created from the video and the variables from the sensors. The results showed that physiological signals closely followed the stress metric provided by the video coders.

The results of these three methods coincided in classifying the driver's stress and showed that stress levels could be recognized by measuring the physiological signals and analyzing them by pattern recognition algorithms. Similarities and differences between this study and our study on recognizing driving-related emotions/states were discussed in Section 4.2.

**Table 1**
Sensors used to measure the physiological signals.

| Physiological signal | Sensor |
|---|---|
| Skin conductance | Skin conductance (SC) sensor |
| Heart activity | Blood volume pressure (BVP) sensor |
| | Electrocardiograph (EKG) sensor |
| Respiration | Respiration sensor |
| Muscle activity | Electromyogram (EMG) sensor |
| Finger pressure | Sentograph |

**Table 2**
Participant's report on arousal level and valance of each emotion.

| | Low arousal | High arousal |
|---|---|---|
| Neutral | Neutral | Reverence |
| Positive | Platonic love | Romantic love, joy |
| Negative | Hate | Anger, grief |

## 3. Preliminary emotion elicitation and recognition experiments

Before designing an applied experiment such as the driving simulator experiment we wanted to evaluate the feasibility of emotion recognition through physiology. For this purpose we designed a preliminary experiment where we elicited not the application specific emotions but the emotions that are experienced by people in their regular daily lives [30].

### 3.1. Experiment design

For this experiment we used movie clips and difficult mathematical questions to elicit six emotions – *sadness, anger, surprise, fear, frustration*, and *amusement*. A non-invasive wireless wearable computer BodyMedia SenseWear Armband (Fig. 2) and Polar chest strap (Fig. 3) that works in compliance with the armband were used to collect three different physiological signals of our participants: *galvanic skin response* (GSR), *skin temperature*, and *heart rate*.

Mathematical questions were used to elicit frustration and movie clips were used to elicit the other five emotions. Movie clips were chosen by conducting a pilot study that was guided by the previous research of Gross and Levenson [19]. Movie scenes resulting in high subject agreement at the end of our pilot study were chosen to elicit specific target emotions.

After choosing the multi-modal stimuli for emotion elicitation, movie clips and the mathematical questions were presented to the participants in a power point slide show. The participants' physiological signals were collected while they were watching the slide show and their self reports were collected between each emotion elicitation session.

### 3.2. Machine learning algorithms

Three different algorithms were used to analyze the physiological data collected in the preliminary emotion elicitation experiment: *k*-Nearest Neighbor Algorithm, Discriminant Function Analysis, and Marquardt Backpropagation Algorithm. The following subsections describe those algorithms.

#### 3.2.1. k-Nearest Neighbor Algorithm

*k*-Nearest Neighbor Algorithm (KNN) [32] used two data sets: (1) training data set (to learn the patterns) and (2) test data set (to verify the validity of learned patterns). The training data set contained instances of GSR, skin temperature, and heart rate values and the corresponding emotion class. The test data set was similar to the training data set, except that it did not have the emotion information. In order to classify an instance of a test data into an emotion, KNN calculated the distance between the test data and each instance of the training data set. Let an arbitrary instance $x$ be described by the feature vector $\langle a_1(x), a_2(x), \ldots, a_n(x)\rangle$, where $a_r(x)$ is the $r$th feature of instance $x$. The distance between instances $x_i$ and $x_j$ was defined as $d(x_i, x_j)$ where,

**Fig. 2.** BodyMedia SenseWear Armband.

**Fig. 3.** Polar chest strap.

$$d(x_i, x_j) = \sqrt{\sum_{r=1}^{n}(a_r(x_i) - a_r(x_j))^2} \tag{1}$$

The algorithm then found the $k$ closest training instances to the test instance. The probabilities of the test instance belonging to each emotion group were calculated by dividing the number of instances from each emotion group by $k$:

$$P(\#i) = \frac{\#\text{ of ins. from group } i \text{ among } k \text{ ins.}}{k} \tag{2}$$

$P(\#i)$ indicated the probability of the test instance belonging to group $i$. Then a random number in $[0,1)$ was generated and the emotion group whose probability range covered this random number was mapped to the test data.

For example if $k = 5$ and there were three (3) groups and if among the 5 closest instances 3 of them belonged to group 1, 1 of them belonged to group 2, and 1 of them belonged to group 3 then $P(\#1) = 0.6$, $P(\#2) = 0.2$, and $P(\#3) = 0.2$. Accordingly, the first group's probability range was $[0,0.6)$, the second group's probability range was $[0.6,0.8)$, and the third group's probability range was $[0.8,1)$. If the randomly generated number was 0.5 then the first emotion group was mapped to the test instance, if it was 0.9 then the third group was mapped to the test instance.

The KNN Algorithm was the first to be implemented for emotion recognition purposes in this study. KNN was chosen to be implemented to test the feasibility of performing pattern recognition on physiological signals that were associated with emotions.

#### *3.2.2. Discriminant Function Analysis*

The second algorithm was developed using Discriminant Function Analysis (DFA) [35], which is a statistical method to classify data signals by using linear discriminant functions. DFA was used to find a set of linear combinations (i.e., discriminant functions) of the variables, whose values are as close as possible within groups and as far apart as possible between groups. Thus, a discriminant function is a linear combination of the discriminating variables. In this study's application of discriminant analysis, the groups were the emotion classes and the discriminant variables were the data signals: GSR, skin temperature, and heart rate. The number of discriminant functions needed was determined by finding the minimum of (1) number of groups and (2) number discriminant variables. There were six groups (emotions: sadness, anger, surprise, fear, frustration, and amusement) and three (data signal types: GSR, skin temperature, and heart rate). Therefore, number of functions needed was three.

Let $x_{\text{data}}$ be the average value of a specific data signal. The function used to solve the coefficients was:

$$f_i(x_{\text{gsr}}, x_{\text{temp}}, x_{\text{hr}}) = u_0 + u_1 * x_{\text{gsr}} + u_2 * x_{\text{temp}} + u_3 * x_{\text{hr}} \tag{3}$$

The objective of DFA was to calculate the values of the coefficients $u_0$, $u_1$, $u_2$, and $u_3$ in order to obtain the linear combination. In order to solve for these coefficients, we applied the generalized Eigenvalue decomposition to the between-group and within-group covariance matrices. The vectors gained through this decomposition were used to derive coefficients of the discriminant functions. The coefficients of each function were derived in order to get a maximized difference between the outputs of group means and a minimized difference within the group means. Every function was orthogonal to each other.

#### *3.2.3. Marquardt Backpropagation Algorithm*

The third algorithm used was a derivation of a backpropagation algorithm with Marquardt–Levenberg modification called Marquardt Backpropagation (MBP) [21]. In this technique, first the Jacobian matrix, which contains first derivatives of the network errors with respect to the weights and biases, is computed. Then the gradient vector is computed as a product of the Jacobian matrix $J(x)$ and the vector of errors $e(x)$ and the Hessian approximation is computed as the product of the Jacobian matrix $J(x)$ and the transpose of the Jacobian matrix $J^T(x)$ [21].

Then the Marquardt–Levenberg Modification to the Gauss–Newton method is given by the following equation:

$$\Delta\underline{x} = [J^T(\underline{x})J(\underline{x}) + \mu I]^{-1}J^T(\underline{x})\underline{e}(\underline{x}) \tag{4}$$

When $\mu$ is 0 or a small value, then this becomes the Gauss–Newton method that uses the Hessian approximation. When $\mu$ is a large value, then this equation is a gradient descent with a small step size $(1/\mu)$. The aim is to make $\mu$ converge to 0 as fast as possible, and this is achieved by decreasing $\mu$ when there is a decrease in the error function and increasing it when there is no decrease in the error function. And the algorithm converges when the gradient value reaches below a previously determined value [21]. This algorithm was chosen to be implemented due to its fast converging nature.

### 3.3. Results

Collected physiological signals were normalized in order to minimize the individual differences among participants. The values of each data type were normalized by using the average value of corresponding data collected during the relaxation period for the same participant. For example, Eq. (5) shows how the GSR values were normalized for a specific participant:

$$\text{normalized\_GSR} = \frac{\text{original\_GSR-relaxation\_GSR}}{\text{relaxation\_GSR}} \quad (5)$$

After the normalization, four features (minimum, maximum, mean, and standard deviation) were extracted for each physiological data type, which resulted in a total of 12 features. Three supervised learning algorithms discussed in Section 3.2 were implemented to analyze these 12 features of each data instance: KNN [32], DFA [35], and MBP [21]. The neural network architecture used with the MBP was a multi-layer neural network with 12 input nodes for 12 features and 6 output nodes for 6 emotion groups. The overall classification accuracies of KNN, DFA, and MBP are given in Fig. 4 with corresponding error bars. More detailed recognition accuracies for each specific emotion can be found in [30].

## 4. Driving simulator experiment

Findings from the aforementioned emotion elicitation experiment showed that emotions experienced by people can be recognized by finding patterns in their physiological signals. Designing and conducting an experiment that focuses on a specific application and elicits emotions that are related to driving safety was the next step.

### 4.1. Driving environment

The driving simulator (Fig. 5) operating in virtual reality (Fig. 6) used in our experiment is located in the new Engineering Building of the University of Central Florida (UCF). The simulator was created using virtual reality technologies and is operated by the Center for Advanced Transportation Systems Simulation (CATSS) at UCF. Fig. 7 shows the control room of the simulator.

The various driving scenarios designed to elicit driving-related emotions were run on this simulator. During each session an ongoing video of each driver was recorded for annotation and future facial expression recognition purposes.

### 4.2. Driving simulator experiment scenarios

In order to elicit driving-related emotions a set of scenarios that contained a series of traffic events were created. The events were ordered in a way that they would first elicit panic/fear, then frustration/anger, and finally boredom/fatigue. Baselines were inserted before and after eliciting each emotion and neutrality was elicited through those baselines. Below are the events that were created to elicit each specific emotion:

#### 4.2.1. Panic/fear

While driving downhill in an accident scene, a child suddenly walked to the middle of the road and stopped and the driver hit him unavoidably. Even when the driver tried to avoid hitting the child; the maneuver was prevented by disabling the

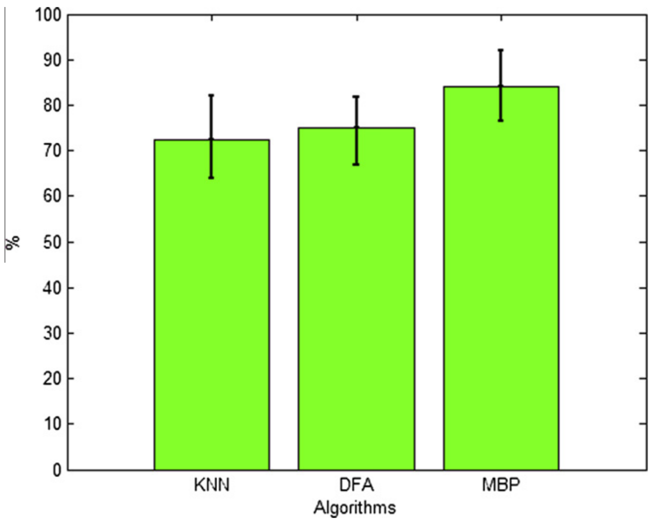


**Fig. 4.** Overall classification accuracies with KNN, DFA, and MBP.

**Fig. 5.** Car operating in virtual reality.

**Fig. 6.** Virtual reality environment.

simulator car's brakes and also by placing barricades to both sides of the road so that the driver could not change lanes (Fig. 8).

#### *4.2.2. Frustration/anger*

After hitting the child, the driver was directed to a city scenario, which was created to elicit frustration/anger. These emotions were elicited through a series of events since only one event would not suffice to elicit the target emotions.

First the driver had to stop in the middle of the road and wait for a couple of men who were carrying a big sheet of glass and who had stopped to talk to a third man they met on the road, thus blocking the road.

After passing the glass carrying men, the driver was instructed to turn right at the next intersection; however driver was blocked by a car that spent an excessive amount of time at the lights to make a right turn.

**Fig. 7.** Control room of the driving simulator.

**Fig. 8.** Child walking to the middle of the road.

When the driver finally turned right, having traveled approximately 20 feet, the road was again blocked with a big garbage truck that was trying to make a 3-point turn and park (Fig. 9). Also, there was a taxi behind the participant's car that honked its horn constantly to annoy the driver.

After passing by the garbage truck that parked, the driver was instructed to turn left at traffic lights. At this point there was a white car in front of the participant's car that was waiting to turn left (Fig. 10). However, as soon as the lights turned to green, several pedestrians started passing across the road and the lights turned to red again before the driver had chance to turn left.

After passing the pedestrians and starting to drive on a narrow road, a bus driver drove right toward the participant's car like they were going to collide. The bus driver turned his wheel at the last moment avoiding an accident; however verbally insulted the driver as he passed by.

*4.2.3. Boredom/fatigue*

After leaving the city where the frustrating events occurred, the participants drove on a straight and long road where no event occurred.


**Fig. 9.** Garbage truck making a 3-point turn.


**Fig. 10.** Waiting for the pedestrians to cross.

#### *4.2.4. Baseline (for neutrality)*

Baseline contained an eventless and enjoyable drive between the emotion eliciting events.

One of the biggest differences between Healey's work [22] and our own research was the driving environments. In Healey's experiments real-life traffic was used as opposed to a simulator in a virtual reality. A virtual reality environment provides a totally controlled environment and the advantages of this controlled environment over the unpredictable real-life traffic environment are:

- Every participant experiences the exact same events, which makes it possible to do comparisons between the participants and derive general results.
- Distracters such as noise and motion that influence the physiological signals are kept equal within each scenario including the baselines, which makes it possible to capture the changes in responses that are only due to the changes in emotional states of the participants.

### 4.3. Driving simulator experiment setup

#### 4.3.1. Sample

The sample included 41 students (both undergraduate and graduate) enrolled in UCF. There were 5 females and 36 males and their ages ranged from 18 to 55. Specific ages were not requested; therefore, a mean age was not calculated.

#### 4.3.2. Procedure

One subject participated in the study during each session. After signing the consent forms and filling out the pre-study questionnaires, the non-invasive BodyMedia SenseWear Armband (Fig. 2) was placed on the participants' left arm (to collect galvanic skin response and temperature values). After the armband was activated the Polar chest strap (Fig. 3) that works in compliance with the armband was placed on the participants' chest (to collect heart rate values). Once the chest strap signaled that it had started communicating with the armband the participants were told the following: (1) They would be driving a Saturn car that in a virtual reality environment had an automatic transmission. (2) They were expected to obey the regular traffic rules such as not driving over the speed limit and stopping at red lights and stop signs. (3) The red and yellow arrows on the simulator screen would show them which way to turn (4) The car had motion and as a result it could cause motion sickness. In case that happened they should stop the car and not continue the experiment.

After the participants took their places in the driving seat of the simulator car, they were told the following: (1) to fasten their seat belts, (2) to start the car by turning on the ignition key, and (3) to put the gear in 'D' (Drive) and start driving. The driving simulator scenarios discussed in Section 4.2 was activated once they turned the ignition key to 'on'. While the participants were driving the car, a video of their faces were recorded with a digital camcorder that was mounted on the dash of the simulator car. These videos were saved for future facial expression recognition studies. The scenarios lasted for 12–16 min depending on the driving speed of each participant. The simulator informed the participants vocally when the scenarios were over. After they put the gear in park, stopped and left the car, chest straps and armbands were removed and the data collected in the armbands were downloaded to a computer. Finally the participants were asked to fill out the post-study questionnaire. After the post-study questionnaires were collected the participants were thanked for their time and for joining the study and they were asked if they had any questions.

#### 4.3.3. Measures

The pre-questionnaire included demographic questions about profession, gender, age range, participants' driver's license history, and driving frequency of the participants. The post-study questionnaire included seven questions (three on the emotions experienced, one on how realistic the simulator was, and three on the participants' experiences in real-life traffic). Each of the first three questions asked whether the participants experienced the elicited target emotion, the intensity of this emotion on a 6-point scale (6 being highest) if they experienced it, and whether there was another emotion they experienced. The fourth question asked how realistic the participants found the driving simulator on a 6-point scale (6 being highest). Finally, the last three questions asked the participants how often they got frustrated or angry, how often they got panicked or fearful, and how often they got bored while driving on a 6-point scale (1 being never, 6 being always).

### 4.4. Emotion recognition with machine learning

The physiological signals that were measured during the Driving Simulator Experiment were analyzed using *k*-Nearest Neighbor [32] and Marquardt-Backpropagation [21] discussed in Section 3.2.3 and Resilient Backpropagation (RBP) [41] discussed in Section 4.4.2.

#### 4.4.1. Feature extraction

After determining the time slots corresponding to the point in the driving scenarios where the intended emotion was most likely to be experienced, the experiment resulted in the following set of physiological records: 30 for neutrality, 29 for panic/fear, 30 for frustration/anger, and 27 for boredom/sleepiness (total of 116 physiological records) from 34 different participants out of 41 participants. Seven (7) of the 41 participants either did not complete the experiment or physiological data collected from them was missing one or more physiological data signal type. For some of the 34 participants data loss occurred for specific emotions (e.g. for participant #3, only neutrality, panic/fear, and frustration/anger physiological data was complete), which is the reason for having varying numbers of data instances for each emotion group.

Collected data was stored and normalized and the features minimum, maximum, mean, and standard deviation were extracted for each physiological signal type (GSR, temperature, and heart rate). Data was stored in a three dimensional array of real numbers: (1) the subjects who participated in the experiment, (2) the emotion classes (neutrality, panic/fear, frustration/anger, and boredom/sleepiness) and (3) extracted features of data signal types (minimum, maximum, mean, and standard deviation of GSR, temperature, and heart rate).

Each slot of the array consisted of a unique feature of a data signal type, belonging to one participant while s/he was experiencing an emotion. For example, one slot of the array contained the mean value of normalized skin temperature of participant #1 while s/he was experiencing anger. Another slot contained the standard deviation value of normalized GSR of participant #5 while s/he was experiencing sadness.

The corresponding emotions for the data instances were also stored in a three dimensional array: (1) the subjects who participated in the experiment, (2) the emotion classes (neutrality, panic/fear, frustration/anger, and boredom/sleepiness) and (3) four digit binary representation that indicates the emotion group. For example, for neutrality the first value was set to 1 and the rest were set to zero, for panic/fear the second value was set to 1 and the rest were set to 0, etc.

After the four features were extracted for each data type, they were analyzed with the three supervised learning algorithms: KNN [32], MBP [21], and Resilient Backpropagation Algorithm [41]. Fig. 11 shows how emotion recognition is performed by extracting more features and the following section describes the Resilient Backpropagation Algorithm.

#### 4.4.2. Resilient Backpropagation Algorithm

Resilient Backpropagation Algorithm (RBP) [41] was a derivation of a backpropagation algorithm, where the magnitude of the derivative of the performance function had no effect on the weight update and only the sign of the derivative was used to determine the direction of the weight update. When the derivative of the performance function had the same sign for two consecutive iterations, the update value for each weight was increased and when the derivative of the performance function changed sign from the previous iteration, the update value was decreased. No change was made when the derivative was equal to 0.

Each weight and bias value $X$ was adjusted according to the following formula:

$$dX = \Delta X * sign(gX), \tag{6}$$

where the elements of $\Delta X$ were all initialized to the initial $\Delta$ and $gX$ was the gradient value. The elements of $\Delta X$ are modified after each iteration. If $gX$ had the same sign with the previous iteration then corresponding $\Delta X$ was incremented and if $gX$ changes sign from the previous iteration, then the corresponding $\Delta X$ is decremented.

#### 4.4.3. Emotion recognition accuracy with KNN, MBP, and RBP

The data was first analyzed with KNN [32] and MBP [21] algorithms. The architecture used with the MBP Algorithm was a multi-layer neural network consisting of an input layer with 12 nodes (number of extracted features), a hidden layer with 9 nodes, and an output layer with 4 nodes (number of emotion groups). We did not have enough data instances to use in order to optimize the parameters of the neural network such as the number of hidden nodes; therefore the number of hidden nodes used was not optimized. The number of hidden nodes (9) was chosen randomly among the numbers between the number of input nodes (12) and the number of output nodes (4). The transfer functions used with the architecture were logarithmic sigmoid transfer function and saturating linear transfer function with the hidden nodes and the output nodes respectively.

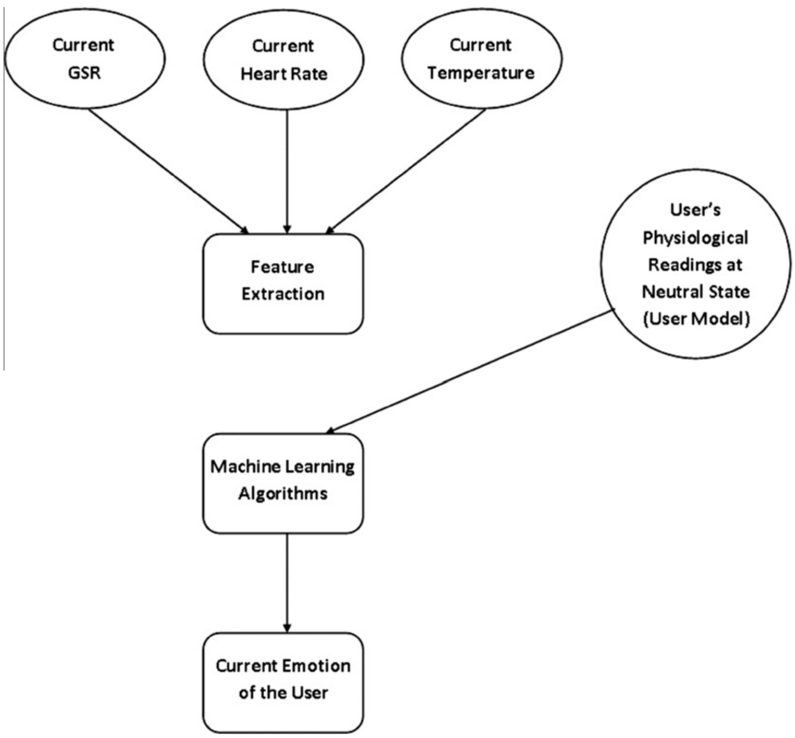


**Fig. 11.** Emotion recognition with feature extraction.

A total of 116 usable (i.e., without data loss) physiological records of GSR, temperature, and heart rate values were collected from the participants for four emotion groups. Twelve features (four for each data signal type) were extracted for each of the physiological record. As a result, a set of 116 data instances to train and test the KNN algorithm or the neural network was obtained.

Both the KNN algorithm and the neural network with MBP were trained by leave-one-out method (every time KNN and the network with MBP were trained, data from one participant was left out). As a result they were trained with 34 different data sets. Each one of the data sets included all the instances except these that belonged to a specific participant. Therefore, the number of instances in each data set was equal to the number of all instances (116) minus the number of instances that belonged to a specific participant (1–4 depending on the data loss). Then the KNN algorithm's and neural network's performances were tested on the instances that were left out. This enabled us to test the performance of the algorithms on test data belonged to a participant that had not been seen before. As a result of having 4 nodes on the output layer, the neural network could be tested every time for all possible outputs.

KNN [32] algorithm and the neural network with MBP were trained and tested with MBP 50 times for each of 34 different training and test data sets. For the neural network with MBP a different set of random initial weights was used at each run. Tables 3 and 4 show the average, minimum, maximum, and standard deviation of correctly classified instances over 50 runs with KNN and MBP algorithms respectively. Figs. 12 and 13 show the average recognition accuracies over 50 runs with error bars, for KNN and MBP algorithms respectively.

**Table 3**
Emotion classification accuracy with KNN for each emotion (over 50 runs).

| | Total instances | Correctly classified instances (average) | Correctly classified instances (min–max) | Correctly classified instances (st. dev.) | Average accuracy (%) |
|---|---|---|---|---|---|
| Neutrality | 30 | 20.06 | 18–23 | 1.54 | 66.87 |
| Panic/fear | 29 | 21.92 | 20–24 | 1.50 | 75.59 |
| Frustration/anger | 30 | 21.12 | 19–23 | 1.41 | 70.40 |
| Boredom | 27 | 12.22 | 9–16 | 2.08 | 45.26 |

**Table 4**
Emotion classification accuracy with MBP for each emotion (over 50 runs).

| | Total instances | Correctly classified instances (average) | Correctly classified instances (min–max) | Correctly classified instances (st. dev.) | Average accuracy (%) |
|---|---|---|---|---|---|
| Neutrality | 30 | 21.84 | 20–23 | 1.11 | 72.80 |
| Panic/fear | 29 | 24.14 | 23–26 | 1.03 | 83.24 |
| Frustration/anger | 30 | 20.26 | 17–22 | 1.59 | 67.53 |
| Boredom | 27 | 18.74 | 17–21 | 1.44 | 69.41 |

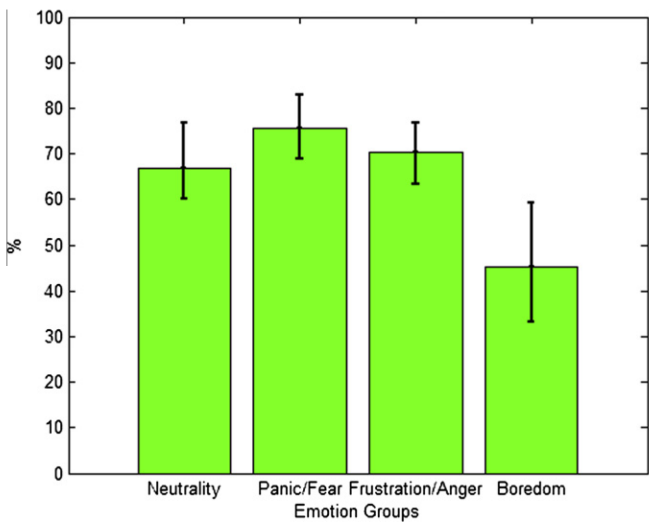


**Fig. 12.** Emotion classification accuracy with KNN for each emotion.

As can be seen from Table 4 and Fig. 13, the MBP algorithm was not as successful as it was in recognizing the six emotions elicited in emotion elicitation experiment with movie clips. This is the reason why RBP [41] algorithm was implemented.

The neural network architecture trained by the RBP algorithm had the same number of input, output, and hidden nodes as the one trained with the MBP algorithm. The transfer functions used with the neural network with RBP were hyperbolic tangent sigmoid transfer function and logarithmic sigmoid transfer function with the hidden nodes and the output nodes respectively. The same leave-one-out method and the same experimental design were used for the architectures that were trained with both MBP and RBP.

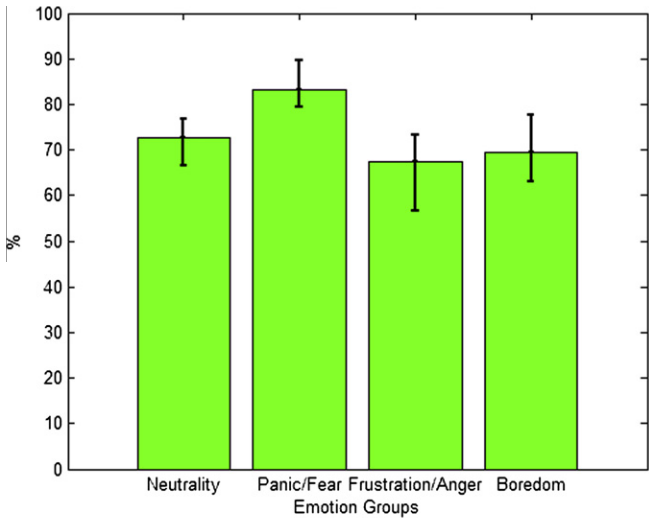


**Fig. 13.** Emotion classification accuracy with MBP for each emotion.

**Table 5**
Emotion classification accuracy with RBP for each emotion (over 50 runs).

| | Total instances | Correctly classified instances (average) | Correctly classified instances (min–max) | Correctly classified instances (st. dev.) | Average accuracy (%) |
|---|---|---|---|---|---|
| Neutrality | 30 | 20.76 | 19–23 | 1.46 | 72.80 |
| Panic/fear | 29 | 26.24 | 25–28 | 1.10 | 83.24 |
| Frustration/anger | 30 | 27.94 | 27–29 | 0.82 | 67.53 |
| Boredom | 27 | 20.88 | 19–22 | 1.04 | 69.41 |

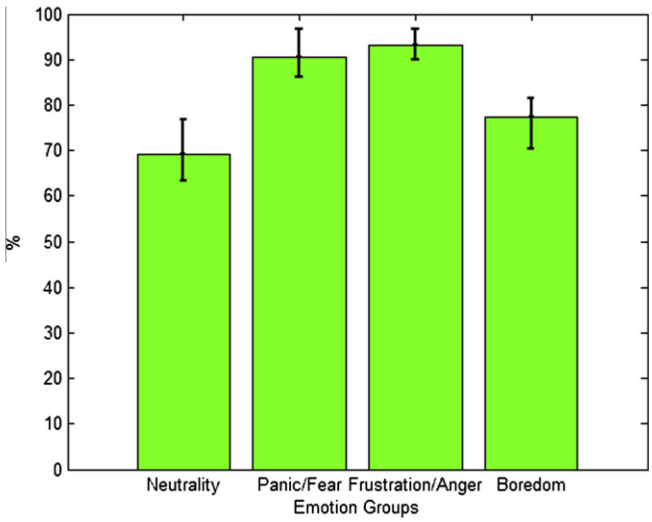


**Fig. 14.** Emotion classification accuracy with RBP for each emotion.

**Table 6**
Emotion classification accuracy with KNN, MBP, and RBP for all emotions.

| | Total instances | Correctly classified instances (average) | Average accuracy (%) |
|---|---|---|---|
| KNN | 116 | 75.32 | 65.93 |
| MBP | 116 | 84.98 | 73.26 |
| RBP | 116 | 95.82 | 82.60 |

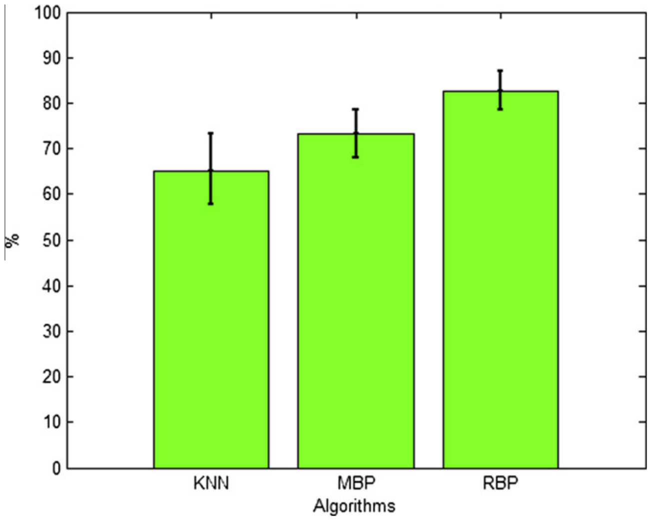


**Fig. 15.** Overall classification accuracy with KNN, MBP, and RBP.

Table 5 shows the average, minimum, maximum, and standard deviation of correctly classified instances over 50 runs with RBP algorithm. Fig. 14 shows the average recognition accuracy over 50 runs with error bars, for the RBP algorithm. Our results show that the RBP algorithm outperformed both the KNN and the MBP algorithms. We believe the improvement in performance provided by Resilient Backpropagation Algorithm was due to the fact that the learning parameters are adapted during the learning process and as a result RBP was not sensitive to the initial selection of these learning parameters [41]. Table 6 and Fig. 15 report the overall emotion classification accuracy of KNN, MBP, and RBP algorithms for all emotion groups over 50 runs.

## 5. User modeling

A use model is defined as "the description and knowledge of the user maintained by the system" [36]. An adaptive system should modify the user model as the individual user changes, because each individual user's responses are different from other users' while interacting with an intelligent system and even same specific user may change their behavior during the interaction [36]. This makes it necessary to build user models that will enable the system to record relevant user information to be able interact with its users appropriately.

Conventional user models were built on what the user knew or did not know about the specific context, what her/his skills and goals were, and her/his self-report about what s/he liked or disliked. The applications of this traditional user modeling include e-learning, web search, health care, e-commerce, and user guidance systems [3,4,8,24,31,42,47,51]. None of those conventional user models included a very important component of human intelligence: affect and emotions.

Our approach for building affectively intelligent and adaptive car interfaces is twofold: recognizing drivers' emotional states and adapting to those emotional states accordingly. After recognizing the user's emotions successfully with the pattern recognition algorithms, and giving feedback to them about their emotional state, the next step was adapting the system to the user's emotional state by considering the current context and user dependent specifics, such as user's preferences and personality traits. Bayesian Belief Networks (BBN) [37] formalization was employed to create these user models to enable the interface to adapt its interaction for each individual user. Fig. 16 presents the complete user interaction and emotion recognition system integrated with affective user modeling for the driving safety application.

### 5.1. Bayesian Belief Networks

Bayesian Belief Networks (BBN) (also known as Bayesian Network or probabilistic causal network) were used to build the user modeling in this system. Bayesian Belief Networks [37] are directed acyclic graphs (DGA), where each node represents a

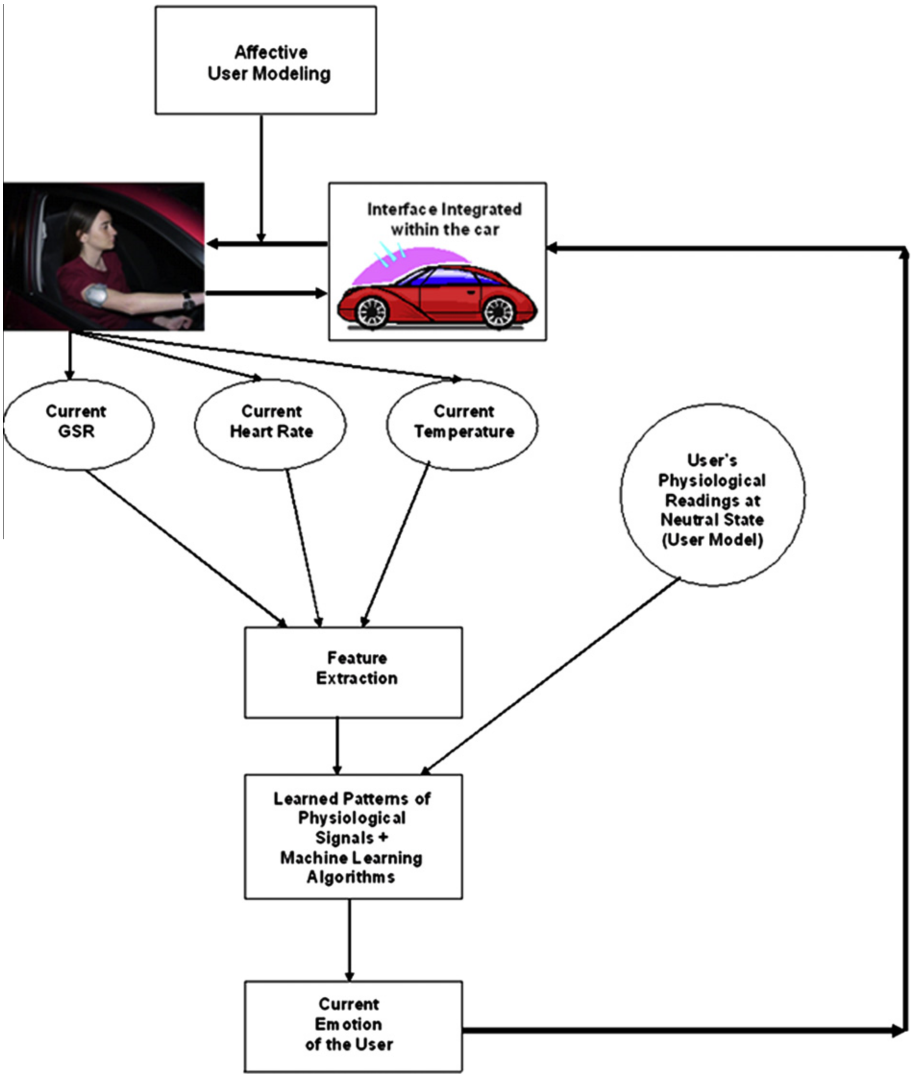


**Fig. 16.** Interaction with user modeling.

random discrete variable or uncertain quantity that can take two or more possible values. The directed arcs between the nodes represent the direct causal dependencies among these random variables. The conditional probabilities that are assigned to these arcs determine the strength of the dependency between two variables.

A Bayesian Belief Network can be defined by specifying:

1. Set of random variables: $\{X_1,X_2,X_3,\ldots,X_n\}$.
2. Set of arcs among these random variables. The arcs should be directed and the graph should be acyclic. If there is an arc from $X_1$ to $X_2$, $X_1$ is called as the parent of $X_2$ and $X_2$ is called as the child of $X_1$.
3. Probability of each random variable that is dependent on the combination of its parents. For a random variable $X_i$, the set of its parents is represented as par $(X_i)$, and the conditional probability of $X_i$ is defined as:

   $P(X_i \mid \mathrm{par}(X_i))$

4. If a node has no parents unconditional probabilities are used. Unlike the traditional rule-based expert systems, BBNs are able to represent and reason with uncertain knowledge. They can update a belief in a particular case when new evidence is provided.

### *5.2. User modeling with Bayesian Belief Networks*

The Bayesian Belief Network representation of the user model that records related user information (preferences, personality, affective information, etc.) in the driving environment is shown in Fig. 17.

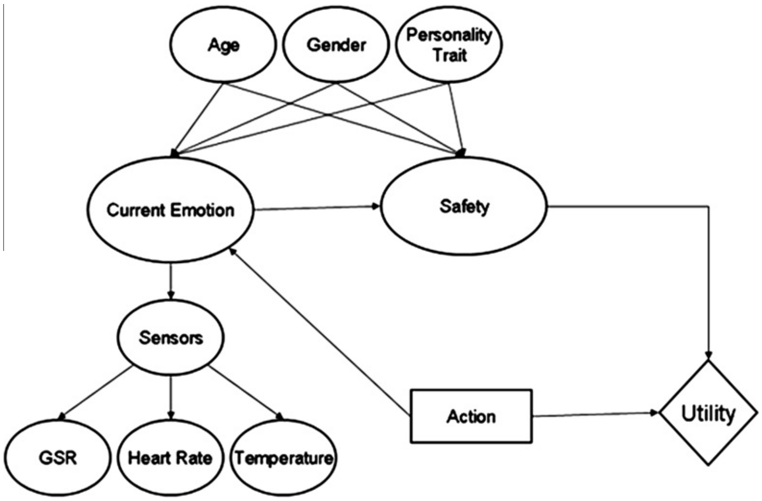


**Fig. 17.** Bayesian Belief Network representation for user model of a driver.

As shown in Fig. 17, the user model for the driving environment was built as a decision support system. There were various parameters that would affect the optimal action that should be chosen by the adaptive interface. These parameters (i.e. nodes of the Belief Network) were:

- Recognized emotion of the driver (e.g. anger, panic, etc.).
- Accuracy of the emotion recognition system (i.e. rate of false negatives and false positives).
- Driver's personality traits (e.g. extravert, open, etc.).
- Driver's previous responses when interacting with the interface (i.e. driver's satisfaction).
- Driver's age.
- Driver's gender.
- Possible actions that can be taken by the interface.

Personality trait, age, and gender were chosen to be included in the model since previous studies suggest that they have influence on how people drive. Possible emotions and states that a driver can experience were chosen as: anger, frustration, panic, boredom, and fatigue and their influence on one's driving are discussed in Section 1.

Personality traits of the driver were included in the user model, because previous studies suggest that personality differences result in different emotional responses and physiological arousal to the same stimuli [23], and the preferences of a person are affected by her personality [34]. Questionnaires can be used in order to successfully identify a driver's personality. Five-Factor-Model was chosen to determine the personality traits [12]. Following are the personality traits based on the Five-Factor-Model:

- Neuroticism (high neuroticism leads to violent and negative emotions and interferes with the ability to handle problems).
- Extraversion (high extravert people work in people oriented jobs, while low extravert people mostly work in task oriented jobs).
- Openness to experience (open people are more liberal in their values).
- Agreeableness (high agreeable people are skeptical and mistrustful).
- Conscientiousness (high conscientious people are hard-working and energetic) [12].

These personality traits influence the way people drive. Cellar et al.'s study [9] showed that Agreeableness had a slight negative correlation with the number of driving tickets and Arthur and Graziano's study [2] showed that people with low Conscientiousness level have higher a risk of being in a traffic accident.

Age and gender also have effect on people's driving [44]. Younger drivers are more prone to being involved in accidents (with a distinguished difference between 18–19-years-olds and 25-years-olds) and more likely to take risks. They display the highest driving violation rates and associate a lower level of risk perception. In contrast, older drivers tend to show a greater frequency of drowsy driving and are more likely suffer from visual impairments that affect their driving [44]. When it comes to gender differences, men are most likely to have accidents because of rule violations, and they make up the majority of aggressive drivers. Women on the other hand, are most likely to be involved in accidents caused by perceptual or judgmental errors and they have the lowest driving confidence [44].

The node *Action* (represented by *A*) represents the possible actions (states) that can be taken by the interface. These actions include:

- Change the radio station.
- Suggest the driver to stop the car and rest.
- Roll down the window.
- Suggest the driver to do a relaxation exercise.
- Tell the driver to calm down.
- Make a joke.
- Splash some water on the driver's face.

The node *Utility* (represented by *U*) represents the possible outcomes of the interface's chosen action in terms of an increase in the safety of the driver. The node is called the utility node, and the outcomes are called utilities. The three possible outcomes are:

- $-1$ (decrease in safety, i.e. decrease in probability for no accident),
- 0 (no change),
- 1 (increase in safety, i.e. increase in probability for no accident).

For example, if the driver was angry and the interface's action was suggesting the driver to perform a relaxation exercise, and if this made the driver angrier, the outcome was $-1$. The variables determining this outcome are *Safety* and *Action*.

The posterior probability for *Safety* is calculated and it is used to calculate the expected utility of choosing each action. The action yielding the highest expected utility is chosen as the interface's action. The formula for the posterior probability of each state of *Safety* is given by:

$$P(S_i|E,P,A,G) = \frac{P(E,P,A,G|S_i)P(S_i)}{P(E,P,A,G|S_1)P(S_1) + P(E,P,A,G|S_2)P(S_2)} \tag{7}$$

The formula for the expected utility of each action is given by:

$$EU(A_i) = U(S_1,A_i)P(S_1|E,P,A,G) + U(S_2,A_i)P(S_2|E,P,A,G) \tag{8}$$

Bayesian Belief Networks was chosen to model the users in the driving environment because of the BBN's ability to represent uncertain knowledge. There were five nodes (events) that affected the action that could be chosen by the adaptive interface. Each of these events could occur in several different ways (for example recognized emotion might be anger, boredom, or panic or user's personality trait one of the five described above), which leads to hundreds of different possible combinations of events thus hundreds of different possibilities for choosing the optimal interface action. This model will be complete when an expert or experts provide the missing knowledge in the form of causal dependencies among the variables.

## 6. Discussion

### 6.1. Summary

To relate physiological signals to driving-related emotions, a driving experiment was designed and conducted in a highly controlled virtual reality environment as opposed to a real-life traffic environment. This controlled virtual reality environment enabled all the participants to experience the exact same events, thus making it possible to do comparisons between the participants and derive general results. Virtual reality also enabled us to keep the distracters such as noise and motion that influence the physiological signals equal within each scenario including the baselines, thus making it possible to capture the changes in responses that were only due to the changes in emotional states of the participants. Another advantage provided by the virtual reality environment was that allowed us to design an experiment with scenarios that would not be possible to design in a real-life traffic environment. For example, generating a panic/fear scenario with a similar accident in real traffic would be impossible and generating a similar frustration/anger scenario would be very hard and expensive. Unfortunately, since we have not designed the equivalent of this experiment in real-life traffic we don't know whether the drivers' experiences of the emotional states would be different in those events. Depending on the event encountered by the driver in the real traffic the intensity of the specific emotion experienced by the driver might be higher or lower when compared to the intensity of the same emotion experienced by the driver in our driving simulator experiment. Our algorithms focused on recognizing the specific emotion, but not its intensity. Future work includes recognizing the intensity levels of the emotional states, therefore our intelligent computer systems would be adapting to different intensities differently.

The driving simulator experiment discussed in this article consisted of various traffic events and was created to elicit panic/fear, frustration/anger, and boredom/fatigue from the participants. BodyMedia SenseWear Armband and Polar chest strap were used to measure galvanic skin response, heart rate, and skin temperature. *k*-Nearest Neighbor (KNN), Marquardt Backpropagation (MBP), and Resilient Backpropagation [RBP] Algorithms were used to classify the physiological signals into corresponding emotions. Overall, KNN could classify these three emotions with 65.33%, MBP could classify them with 73.26% and RBP could classify them with 82.6% accuracy.

**Table 7**
Consequences related to emotion recognition.

| Emotion experienced | Emotion recognized | Consequence |
|---|---|---|
| Yes | Yes | Accurate emotional state recognition |
| Yes | No | False negative |
| No | Yes | False positive |
| No | No | Accurate emotional state recognition |

### *6.2. Conclusion and future work*

An important issue while evaluating the performance of the algorithms in real-life applications is the rate of false negative results (i.e. system does not recognize the negative emotional state of the user) and false positive results (i.e. system recognizes a negative emotional state of the user although she is not experiencing this state) obtained by analyzing the physiological signals of the user. Table 7 summarizes the results that can be obtained while performing emotion recognition.

Due to the nature of emotion recognition problem, it is impossible to prevent all false negatives and false positives; however the rate of false negatives and false positives can be decreased by implementing various techniques. One of these techniques is combining different pattern recognition algorithms for higher recognition accuracy. Another useful technique to increase recognition accuracy might be integrating different modalities that the emotions can be recognized from such as physiology, facial expressions, and vocal intonation.

All experiments discussed in this article were conducted in controlled environments and during all those experiments, physiological data was analyzed after the experiment was completed. An important next step will be collecting physiological data during real-life situations and analyzing it and performing emotion recognition in real-time. Another improvement to our study will be applying different feature extraction techniques and combining different pattern recognition algorithms for increased accuracy in emotion recognition.

## References


[1] J.H. Abawajy, Human–computer interaction in ubiquitous computing environments, International Journal of Pervasive Computing and Communications 5 (1) (2009) 61–77.
[2] W. Arthur, W.G. Graziano, The five-factor model, conscientiousness, and driving accident involvement, Journal of Personality 64 (1996) 593–618.
[3] R.S.J.d. Baker, A.T. Corbett, I. Roll, K.R. Koedinger, Developing a generalizable detector of when students game the system, User Modeling and User Adapted Interaction 18 (2008) 287–314.
[4] T. Barker, S. Jones, J. Britton, D. Messer, The use of a co-operative student model of learner characteristics to configure a multimedia application, User Modeling and User-Adapted Interaction 12 (2002) 207–241.
[5] N. Bianchi, C.L. Lisetti, Modeling multimodal expression of user's affective subjective experience, User Modeling and User-Adapted Interaction 12 (2002) 49–84.
[6] R.L. Birdwhistle, Kinesics and Context: Essays on Body Motion and Communication, University of Pennsylvania Press, 1970.
[7] G. Bower, Mood and memory, American Psychologist 36 (2) (1981) 129–148.
[8] F. Carmagnola, F. Cena, User identification for cross-system personalization, Information Sciences 179 (2009) 16–32.
[9] D.F. Cellar, Z.C. Nelson, C.M. Yorke, The five-factor model and driving behavior: personality and involvement in vehicular accidents, Psychological Results 86 (2000) 454–456.
[10] D.M. Clynes, Sentics: The Touch of the Emotions, Anchor Press, Doubleday, 1977.
[11] J.A. Colquitt, J.A. LePine, R.A. Noe, Toward an integrative theory of training motivation: a meta-analytic path analysis of 20 years of research, Journal of Applied Psychology 85 (2000) 678–707.
[12] P.T. Costa, R.R. McCrae, The Revised NEO Personality Inventory (NEO PI-R) Professional Manual, Psychological Assessment Resources, Odessa, FL, 1992.
[13] A. Damasio, Descartes' Error, Avon Books, New York, NY, 1994.
[14] D. Derryberry, D. Tucker, Neural mechanisms of emotion, Journal of Consulting and Clinical Psychology 60 (3) (1992) 329–337.
[15] P. Ekman, R.W. Levenson, W.V. Friesen, Autonomic nervous system activity distinguishes between emotions, Science 221 (4616) (1983) 1208–1210.
[16] N.H. Frijda, The Emotions, Cambridge University Press, New York, 1986.
[17] R. Fuller, J.A. Santos (Eds.), Human Factors for Highway Engineers, Elsevier Science, Oxford, UK, 2002.
[18] D. Goleman, Emotional Intelligence, Bantam Books, New York, 1995.
[19] J.J. Gross, R.W. Levenson, Emotion elicitation using films, Cognition and Emotion 9 (1995) 87–108.
[20] J.J. Gross, R.W. Levenson, Hiding feelings: the acute effects of inhibiting negative and positive emotions, Journal of Abnormal Psychology 106 (1) (1997) 95–103.
[21] M.T. Hagan, M.B. Menhaj, Training feedforward networks with the Marquardt algorithm, IEEE Transactions on Neural Networks 5 (6) (1994) 989–993.
[22] J. Healey, Wearable and Automotive Systems for Affect Recognition from Physiology, PhD Thesis, Massachusetts Institute of Technology, May 2000.
[23] L. James, D. Nahl, Road Rage and Aggressive Driving: Steering Clear of Highway Warfare, Prometheus Books, Amherst, NY, 2000.
[24] X. Jiang, A. Tan, Learning and inferencing in user ontology for personalized semantic web search, Information Sciences 179 (2009) 2794–2808.
[25] J. Larson, C. Rodriguez, Road Rage to Road-Wise, Tom Doherty Associates, Inc., New York, NY, 1999.
[26] J. Ledoux, Brain mechanisms of emotion and emotional learning, Current Opinion in Neurobiology 2 (1992) 191–197.
[27] W. Liao, W. Zhang, Z. Zhu, Q. Ji, W. Gray, Toward a decision-theoretic framework for affect recognition and user assistance, International Journal of Human–Computer Studies 64 (2006) 847–873.
[28] C.L. Lisetti, A user model of emotion–cognition, in: Proceedings of the UM'99 Workshop on Attitude, Personality, and Emotions in User-Adapted Interaction, Banf, Canada, June 1999, pp. 307–309.
[29] C.L. Lisetti, F. Nasoz, MAUI: a multimodal affective user interface, in: Proceedings of the ACM Multimedia International Conference, Juan les Pins, France, December 2002, pp. 161–170.

[30] C.L. Lisetti, F. Nasoz, Using non-invasive wearable computers to recognize human emotions from physiological signals, EURASIP Journal on Applied Signal Processing 11 (2004) 1672–1687 (special issue on Multimedia Human–Computer Interface).
[31] W. Liu, F. Jin, X. Zhang, Ontology-based user modeling for e-commerce system, in: Proceedings of ICPCA'08, Third International Conference on Pervasive Computing and Applications, Alexandria, Egypt, October 2008, pp. 260–263.
[32] T.M. Mitchell, Machine Learning, McGraw-Hill Companies Inc., 1997.
[33] F. Nasoz, M. Bayburt, Affectively intelligent user interfaces for enhanced e-learning applications, in: M. Kurosu (Ed.), Human Centered Design, HCII 2009, LNCS, vol. 5619, Springer-Verlag, Berlin, Heidelberg, 2009, pp. 765–774.
[34] C. Nass, K.M Lee, Does computer-generated speech manifest personality? An experimental test of similarity-attraction, in: Proceedings of the CHI 2000 Conference, The Hague, The Netherlands, April 1–6, 2000, pp. 329–336.
[35] A.A. Nicol, P.M. Pexman, Presenting Your Findings: A Practical Guide for Creating Tables, American Physiological Association, Washington, DC, 1999.
[36] A.F. Norcio, J. Stanley, Adaptive human–computer interfaces: a literature survey and perspective, IEEE Transactions on Systems, Man, and Cybernetics 19 (2) (1989) 399–408.
[37] J. Pearl, Probabilistic Reasoning in Expert Systems: Networks of Plausible Inference, Morgan Kaufmann Publishers, Inc., San Francisco, CA, 1988.
[38] C. Peter, R. Beale, Affect and Emotion in Human–Computer Interaction: From Theory to Applications, Springer-Verlag, Berlin, Heidelberg, 2008.
[39] R.W. Picard, E. Vyzas, J. Healey, Toward machine emotional intelligence analysis of affective physiological state, IEEE Transactions on Pattern Analysis and Machine Intelligence 23 (10) (2001) 1175–1191.
[40] B. Reeves, C.I. Nass, The Media Equation: How People Treat Computers, Television, and New Media Like Real People and Places, Cambridge University Press, Cambridge, 1996.
[41] M. Riedmiller, H. Braun, A direct adaptive method for faster backpropagation learning: the RPROP algorithm, in: Proceedings of the IEEE International Conference on Neural Networks, San Francisco, CA, 1993, pp. 586–591.
[42] S.P. Roth, P. Schmutz, S.L. Pauwels, J.A. Bargas-Avila, K. Opwis, Mental models for web objects: where do users expect to find the most frequent objects in online shops, news portals, and company web pages?, Interacting with Computers 22 (2010) 140–152
[43] J. Scheirer, R. Fernandez, J. Klein, R.W. Picard, Frustrating the user on purpose: a step toward building an affective computer, Interacting with Computers 14 (2) (2002) 93–118.
[44] UK Department for Transport, Department for Transport, International Review of the Individual Factors Contributing to Driving Behavior, Technical Report, Department for Transport, October 2003.
[45] A.V. Vasilakos, W. Pedrycz, Ambient Intelligence, Wireless Networking, Ubiquitous Computing, Artech House, MA, 2006.
[46] O. Villon, C.L. Lisetti, Toward Building Adaptive User's Psycho-Physiological Maps of Emotions Using Bio-Sensors, Emotion and Computing at KI 2006, 29th Annual Conference on Artificial Intelligence, Bremen, Germany, June 14–19, 2006, pp. 35–38.
[47] J.R. Warren, H.K. Frankel, J.T. Noone, Supporting special-purpose health care models via adaptive interfaces to the web, Interacting with Computers 14 (2002) 251–267.
[48] J.H. Westerink, M. Ouwerkerk, T.J.M. Overbeek, W.F. Pasveer, B. Ruyter, Computing emotion awareness through galvanic skin response and facial electromyography, Probing Experience 8 (2008) 149–162.
[49] R. Zajonc, On the primacy of affect, American Psychologist 39 (1984) 117–124.
[50] Z. Zhai, A. Barreto, Stress recognition using non-invasive technology, in: Proceedings 19th International Florida Artificial Intelligence Research Society Conference (FLAIRS 2006), Melbourne Beach, Florida, May 11–13, 2006, pp. 395–400.
[51] A. Zimmermann, A. Lorenz, LISTEN: a user-adaptive audio-augmented museum guide, User Modeling and User Adapted Interaction 18 (5) (2008) 389–416.