Emotional Adaptive Vehicle User Interfaces: moderating negative effects of failed technology interactions while driving

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ABSTRACT
Automotive Natural User Interfaces have the potential to increase user experience providing intuitive interactions for drivers. However, in the complex setting of a driving vehicle, failed interactions with in-vehicle technology can lead to frustration and put drivers in a dangerous situation. This paper evaluates the possibility of applying emotion recognition to vehicular spoken dialogue systems in order to adapt the dialog strategies, in error recovery scenarios. An emotional taxonomy is developed for the interactions with a conversational vehicular application, the Voice User Help. The positive results of the performance of VUH emotion recognizer support the creation of real-time classification of the user emotional state, which serves as basis to emotional reappraisal dialog strategies that mitigate negative effects on the driver's cognitive load and driver performance.

Categories and Subject Descriptors
H.5.2 [User Interfaces]: Input devices and strategies, Interaction styles, Natural language, Voice I/O.

General Terms
Measurement, Performance, Design, Experimentation, Human Factors.

Keywords
Voice User Help, Natural User Interfaces, Voice User Interfaces, Affective Computing, Adaptive Interfaces

1. INTRODUCTION
Research in the automotive field has demonstrated that drivers are increasing technology interactions while driving. The use of In-vehicle Infotainment Systems (IVIS), as well as plug-in consumer electronics like smartphones has peaked considerably in recent years [1]. The negative effects of these interactions have raised safety concerns since research has demonstrated that the use of IVIS's increases 25-30% the crash risk [2].

In order to improve driver performance while interacting with in-vehicle technologies, some researchers have looked at Natural User Interfaces (NUI). NUIs have the potential to increase user experience by looking at interaction techniques such as touch, gestures, speech, or full body movements that feel like an extension of a everyday practices [3].

But even when in-vehicle technologies apply natural user interfaces, interactions are not flawless, especially in the complex settings of the moving vehicle. If the output of the interaction is not the expected, users might become irritated or enraged. On the other hand, they might be delighted if the system helps them complete a difficult task successfully. Rosalind Picard introduced these considerations for intelligent computer systems in the nineties by creating the field of *Affective Computing* [4]. Since then, a number of approaches have been developed to create computer programs that are able to recognize and react to emotional states.

This paper evaluates the possibility of applying emotion recognition to vehicular spoken dialogue systems. It is believed that the emotional state of the driver is related to her/his cognitive load and the resources allocated to context awareness. Therefore, the emotional state of the driver can provide useful information to adapt the dialog strategies, especially in the case of unfruitful interactions.

The rest of the paper briefly reviews emotion related automotive research, presents the Voice User Help (VUH), a conversational in-vehicle application, explains an emotional taxonomy developed for the VUH, presents results on emotion recognitions and introduces indications toward using emotional adaptive user interfaces to palliate negative effects during error recovery.

2. AFFECTIVE COMPUTING IN AUTOMOTIVE RESEARCH
Traditionally, emotional taxonomies developed for automotive environments have paid attention to negative emotions that may arise during the driving experience, such as anger that results in road rage behaviors, fatigue and boredom. All these emotions are probable outcomes after long periods of driving or can be consequence of the stress generated during dense traffic situations. Jones and Jonsson studied the affective cues of drivers from spoken interactions with in-car dialog systems. The recorded driver utterances were analyzed by a group of experts and classified into the following taxonomy: boredom, sadness, anger, happiness and surprise [5]. Boril studied the speech production variation during driver interaction with in-vehicle commercial dialog systems. However, his work only considered a neutral and negative emotion classification [6]. Similarly, Wood studied conversations in a driver simulator where participants were asked to give their opinions on topics believed to produce neutral

emotions and topics that conveyed intense (negative) emotions such as death penalty or terrorism [7]. Eyben's general review of affective computing applied to automotive environments discusses the influence of affective states in driving performance with the purpose of identifying main factors for developing counter-steering strategies aiming to position the emotional state of the driver in a neutral / happy state [8]. Eyben proposes an emotional taxonomy for automotive environments where basic emotional states are mixed with other affective states such as moods identifying psychological states that might lead to driver distraction. Therefore, he includes in his taxonomy anger, aggressiveness, fatigue, stress, confusion, nervousness, sadness, boredom and happiness. Grimm studied the effects of positive and negative emotional feedback from the application on driver performance [9].

Other emotional taxonomies for automotive environments have been included in the design of vehicular ontologies in which user modeling is an important part. Feld and Müller introduce in their Automotive Ontology an "emotional state class" with the following possible values: happiness, anxiety, anger, disgust and sadness. Besides the Emotional State they include a mental state characterized by time pressure, level of cognitive load, nervousness and irritation [10]. Islinger identifies in his modeling of the driver's different states based on the recognition of facial expressions. He distinguishes physiological states such as hunger and thirst versus psychological states such as happiness, sadness, anger, anxiety, nervousness, relaxed, bored, stress, attentiveness and drowsiness [11]. These psychological states, originally based on Ekman's [12] and Plutchick's [13] basic emotion taxonomies are adapted to the automotive environment but turn out to be more a collection of emotional and mental states under which someone would need special treatment from an assistive vehicle system, rather than purely emotional states produced as a result of interaction with such a system.

The previously mentioned research has focused on evaluating the effects of emotions in driver performance, rather than reacting to emotional states. Emotions as input parameters for adaptive interfaces in driving environments have not been thoroughly studied since the use of NUIs is a newer field of study. Emotion-related research in the automotive field has, however, supported the notion that "happy drivers are better drivers" [14]. Jeon suggested some emotion adaptation strategies in automotive environments designed to help drivers with Traumatic Brain Injury. He proposes to either modify the emotional state into a desirable emotional state (neutral), using an emotion regulation technique; or attract the complete attention of the driver onto the driving task itself, thus helping the driver to escape from the adverse emotional state [15]. Harris and Nass indicated that positive reappraisal during negative events in the road helped reduce driver frustration and improving driver performance [16]. Other researchers suggest that adapting the system to the same affective state of the user reduces driver distraction [17].

Given the disparity of emotional taxonomies and emotion regulation strategies, an automotive application was created to investigate emotional adaptive natural interfaces.

3. VOICE USER HELP

The Voice User Help (VUH) is a voice-interfaced in-vehicle application that provides vehicle documentation, in the form of informational instructions, using a conversational question-answer interface. The purpose of the application is to overcome the current limitations of in-vehicle manuals and provide user-friendly access to information while driving by means of a user-centered design.

Being a driver assistance system VUH needs to provide intuitive access to information under potentially stressful traffic conditions in which the user can only produce voice inputs and understand simple auditory information. In order to reduce the processing time and effort on the user side the conversational VUH allows natural language input when stating the problems. These inputs typically take the form of questions that the Voice User Help needs to decode, identify and answer. After performing the information search, based on the parameters extracted from the user query, the most optimal answer is presented to the driver. In the case of retrieving the wrong information, an error recovery process analyzes the most plausible cause of the error based on confidence levels of the speech recognizer, the emotional state of the user and the interaction history. Using these parameters the Voice User Help chooses an adapted recovery approach and provides a recommendation on how to reformulate the question for best performance.

4. EMOTIONAL TAXONOMY FOR THE VOICE USER HELP

Given the variety and discordance of emotional taxonomies in the literature, the need to define an emotion classification adapted to a driving environment and the interactions with the Voice User Help was clear. Since VUH can only receive audio input, a group of primary emotions whose attributes were clearly distinguishable from audio data was developed.

Pitterman's taxonomy introduced an adaptive conversational travel agency system [18] that used an adapted emotional taxonomy composed of 7 distinct emotions ranging from negative (anger) to positive (joy). This taxonomy was proposed with the purpose of identifying the user's mental state while interacting with the application. The emotions are ordered in a valence/arousal scale in figure 1. Due to the subjectivity of different emotion theories and the uncertainty of the emotion recognizer the crosses indicate regions where the emotions are located, rather than exact positions.

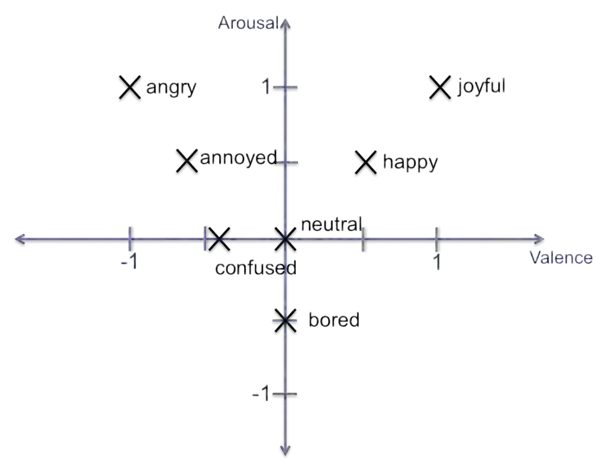

Figure 1 - VUH emotional taxonomy in an arousal/valence scale

Emotions like fear or sadness were ruled out of the taxonomy because they would most likely not be a consequence of the interaction with the VUH. Furthermore, only emotions that provided information for an adaptive interface to modify the interaction were included in the taxonomy. e.g., if the user was in a sad emotional state, the user interface would do a poor job in trying to comfort her/him.

5. EMOTION RECOGNIZER

The emotion recognizer of the VUH used the software Praat v.5.3.03 [19], to extract the prosodic values that conformed the emotional vector and the Weka data mining tool [20] to train each emotion recognition model and evaluate the classification algorithm that might produce the best results.

The emotion was calculated in real time using a Praat script that extracts, Mel frequency cepstral coefficients as well as values of pitch, intensity and power. Mean values and derivatives of each feature comprised the 21-feature vector. Using this data, a speaker dependent recognizer was developed.

Different sample sizes were analyzed to evaluate the minimum sample size needed for an emotional corpus to provide high performance. The results, presented in Table 1, show that even with small emotional data samples a personalized emotion recognizer performs good using Logistic Model Trees (LMT), Multi-Layer Perceptrons and Simple Logistic regression classifiers, around 70% recognition success.

Table 1 - Performance of Weka algorithms on Emotion classification

Algorithm	Training Cases			
	49	98	245	490
Ibk	57.14	61.22	82.45	85.51
LMT	**71.43**	**78.57**	**83.56**	**90.00**
MultiClass Classifier	55.10	68.37	76.73	87.35
Multi-Layer Perceptron	69.39	76.53	85.71	88.98
NaiveBayes	59.18	67.35	76.33	79.39
SimpleLogistic	71.43	78.57	85.31	88.16

The results showed that with a limited number of iterations (less than 500 utterances) the LMT classifier could perform up to 90% accuracy on the 7-emotion taxonomy.

6. HISTORY DIALOG VARIABLES

Besides the real-time emotion recognition during the interactions with the VUH, other dialog history variables help the dialog manager during error recovery scenarios.

A “Connection Error Count” keeps track of the number of connection errors between the front end and the back-end of the application. Establishing a threshold, the application can suggest that the user to terminate the interaction due to errors in the telematics system, and encourage him/her to try again later. This would potentially prevent high levels of driver distraction due to longer and increasingly frustrating interactions.

Furthermore, a “Negative Turns Count” keeps track of the number of wrong answers presented to the user during the application life cycle. Different dialog strategies might take place depending on the increasing value of this variable to adapt the interaction to a growing negative state resulting of unsuccessful searches.

7. DIALOG ADAPTATION STRATEGIES

Using the above-described emotional states and the dialog history variables as inputs, the Voice User Help is able to recognize dangerous interactions that could potentially put the driver at risk and can take the decision to actively interrupt the interaction for safety purposes, or try to apply some emotional regulation technique.

However, it is not yet clear what would be the best approach to deal with emotions while driving in order to assist driver performance and increase user satisfaction. While some research indicates that adjusting the emotional state of the application to the emotional state displayed by the driver will increase user satisfaction as well as reduce driver distraction, others vote for neutralizing any emotional state to a neutral state or rather drive the driver to a positive emotional state.

On going research is looking at the effects on driver performance and cognitive load of emotion matching and emotion neutralization compared to the use of the Voice User Help with no emotion adaptation. Further research questions investigate if during error recovery scenarios informational feedback is preferred to apologetic feedback.

Preliminary results seem to support that emotion neutralization techniques help users under negative emotional states to reduce the cognitive load and improve driver performance while emotional matching techniques help participants experiencing positive emotional states to keep a positive to neutral state during error recovery scenarios. We will also explore new parameters relatives to emotional level.

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