IN-VEHICLE MONITORING OF AFFECTIVE SYMPTOMS FOR DIABETIC DRIVERS
In-vehicle Hypoglycemia Alerting System in EU Project METABO

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Abstract: Can self-management of emotion help on safety driving of diabetic patients? Fluctuant emotions in driving can lead to very critical situations. In particular for diabetic drivers experiencing hypoglycemic events it is inevitable to provide an intelligent alerting/recommendation system that assesses continuously driver's affective and metabolic states and predicts sudden hypoglycemic events, in order for avoiding dangerous situations during driving. In this paper we introduce an innovative approach to in-vehicle emotion monitoring system conceived in the EU project METABO. The system aims for providing the drivers a self-management opportunity to monitor/control their emotional states and apt recommendations according to detected hypoglycemic symptoms.

1 INTRODUCTION

Emotions affect perception, action and internal processes of which the person having the emotion may not be aware. This unawareness is then very dangerous for drivers, since safe driving activity demands various types of driver's abilities simultaneously such as psychomotor skills, visuospatial functions, vigilance and rapid information processing and judgement. Actually, it is reported that the inability to manage one's emotions during driving is identified as one of major causes of road traffic accidents (James, 2000). This is even more critical due to the fact that drivers often lack the ability to calm themselves their negative emotions, for instance, when they are angry or frustrated. There are a number of research results in literature that support the importance of the emotional state of drivers for traffic safety. Lajunen and Parker (Lajunen and Parker, 2001) established the links between anger, aggression and reported accidents. Anxious may impair driver's capability to deal with a complex situation that occurs unexpectedly because anxiety narrows attentional focus, leading to misinterpretation (Öhman, 2000). Furthermore, in the work (Armitage et al., 1999) it is claimed that positive moods promote risky decision making and more heuristic strategies, whereas negative moods instigate a more problem-focussed approach.

The role of fluctuant emotions in driving is more critical for diabetic drivers who suffer from hyper-/hypoglycemia accompanying extremely unsteady affective symptoms. Acute hypoglycemia, the most common side effect of insulin therapy, may compromise driving skills. Functions that are most affected by hypoglycemia include crucial abilities for safe driving such as rapid judgement, attention, analysis of complex visual stimuli, memory and processing of information and hand-eye coordination. Such dysfunctions cause problem with contrast sensitivity and increased irritability and promote anger and mood changes. Particularly, it is important to note that the patients who lose their ability to recognize the early signs of hypoglycemia, called hypoglycemia unawareness, suffer from at least ten times higher risk

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for severe hypoglycemia than that of patients without this hypoglycemia unawareness. The impaired awareness of hypoglycemia is associated with more profound cognitive dysfunction, which takes longer to recover after acute hypoglycemia than is experienced by individuals with normal awareness (Deary, 1999; Gold et al., 1995).

All these findings call to mind the need for in-vehicle emotion monitoring system that observes patient's emotional state during driving, reminds patient to manage his affective state himself, predicts/alerts forthcoming hypoglycemia events and recommends needed activity. Recently many works on automatic emotion recognition using physiological measurements have been reported especially in advanced human-computer interaction (HCI) (Kim and André, 2008). However, as emotion is a function of time, context, space, culture, and person, it's intensity and effect may also widely differ from user to user and from situation to situation. For diabetes mellitus, it needs to pay a special attention to the fact that applying of emotion recognition systems developed based on healthy people might result in a risky situation. This is because of the fact that origin stimuli causing actual emotional state can hardly be traced for diabetes patient, due to mutual interaction between emotional change and the glucose level, which can be described in the form of a vicious circle (i.e. cause-result-cause).

In this paper, we present a design of in-vehicle emotion monitoring system using multichannel biosensors. First we briefly introduce the EU project METABO where we develop the monitoring system as a part of the project. Then we move to summarize the concept of in-vehicle hyperglycemia alerting system and describe our systematical approach to the in-vehicle emotion monitoring system.

2 PROJECT METABO

The METABO[1] (Controlling Chronic Diseases related to Metabolic Disorders) is an european collaborative project funded by European Commission and started in January of 2008 by 22 partners from 9 EU member states.

2.1 Objective of METABO

The aim of METABO is to set up a comprehensive platform, running both in clinical settings and in every-day life environments, for continuous and

[1]EU FP7-ICT-2007-1-216270, www.metabo-eu.org

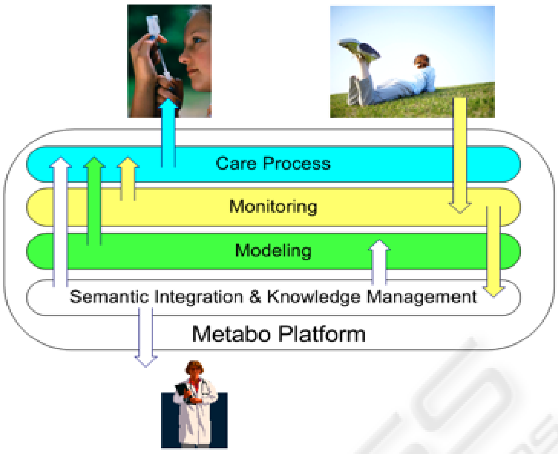

Figure 1: The concept of the METABO (after METABO Annex I "Description of Work").

multi-parametric monitoring of the metabolic status in patients with, or at risk of, diabetes and associated metabolic disorders. The type of parameters that will be monitored, in addition to "traditional" clinical and biomedical parameters, will also include subcutaneous glucose concentration, dietary habits, physical activity and energy expenditure, effects of ongoing treatments, and autonomic reactions. The data produced by METABO will be integrated with the clinical data and the history of the patient and will be used in two major interrelated contexts of care:

1. Setting up a dynamic model of the metabolic behavior of the individual to predict the influence and relative impact of specific treatments and of single parameters on glucose level.
2. Building personalized care plans integrated in the current clinical processes linking the different actors in primary and secondary care and improving the active role of the Patient.
3. The combined use of tools for predictive modelling and for the personalisation of the individual process of care will close the loop between the Patients, the Professionals involved and the Health Organisation. Mining the data produced by METABO will allow the identification of patterns and trends that will allow the fine tuning of the model and the prompt adjustment of the process of care.

METABO consists of a global platform that collects and processes data coming from the patient and the physicians' tools (a mobile device for the patients to acquire data from user and sensors and a web application for the physicians to present them all data collected and analyzed) and works as an information exchange bridge between physicians and patients. On top of this, the system provides both groups of users with decisions support systems to give them recommendations in a personalized short loop and an integrated long loop Figure 2.

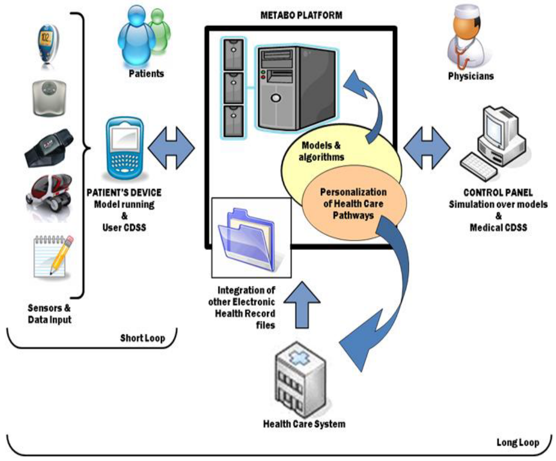

Figure 2: Diagram of METABO Platform (after METABO Annex I "Description of Work").

2.2 In-vehicle Hypoglycemia Alerting System

In-vehicle hypoglycemia alerting system (IHAS) is a special case-study in the METABO, which aims at designing and building an in-vehicle version of the system to provide metabolic monitoring and preventive support to drivers, especially to those suffering from sudden and/or unaware hypoglycemia. This research is innovative in that it aims to measure and predict hypoglycemia events indirectly by using physiological sensors and by analyzing driver's behavior behind the wheel and the change of emotional states. The hypothesis is that hypoglycemia will affect the both the bio-profile of the patient and his/her driving behavior. The IHAS consists of four subsystems, i.e. behavioral monitor, emotive monitor, healthcare state and physiological state:

Behavioral Monitor. This subsystem measures driving-relevant signals such as steering wheel angle, vehicle speed, lateral and longitudinal acceleration, brake usage, etc. These will then be used to develop a module able to evaluate driver's behavior. The final scope will be to identify pattern and trends in these signals which can be correlated to hypoglycemic events in order to alert the driver to the forthcoming hypoglycemia.
Input: car signals available on the CAN networks.
Output: indexes quantifying driver behavior focusing on those behaviors.

Emotive Monitor. This subsystem is responsible for recognizing driver's emotional states by using multichannel physiological signals and visual information. This task includes to verify predictability of glucose level changes based on actual emotional state under the condition of a short-term observation and to provide the driver a possibility of emotion management training through biofeedback. Main challenge of the system is to find interferential correlation between driver's emotional state and the change of glucose level.
Input: multichannel physiological signals and visual information.
Output: driver's emotional states and prediction of hypoglycemic events.

Healthcare Monitor. This subsystem analyzes dietry, physical activity, treatment, and glycemic data and predicts the metabolic status of the diabetic driver in the short- and medium run. The data will be collected by using patient's mobile device (PMD) and continuous glucose monitoring system (CGMS).
Input: treatment history, blood glucose values, insulin intake, food intake, physical activity
Output: predicted blood glucose level and recommendations.

Physiological Monitor. This module analyzes the same physiological signals used for emotive monitor in order for assessing the physiological state of the driver. Particularly, it mainly focuses on extracting cardiac features from electrocardiogram and blood pressure.
Input: multichannel physiological signals
Output: drivers physiological states focusing on hypoglycemia detection.

3 IN-VEHICLE EMOTION MONITORING

Figure 3 shows the frame work of in-vehicle emotion monitoring (IEM) system.

3.1 Biosensors

We collect the physiological signals by using the ME6000[2] with four biosensors, electromyogram (EMG), skin conductivity (SC), electrocardiogram (ECG), and respiration (RSP). The typical waveforms and sensor positions are illustrated in Figure 4.

[2]This is an 16 channel multi-modal Biofeedback system with 14 bit resolution in sampling rate of 2000 Hz. www.megaemg.com

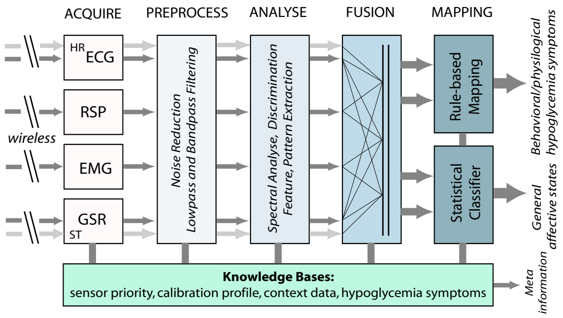

Figure 3: Framework of physiological emotion recognition.

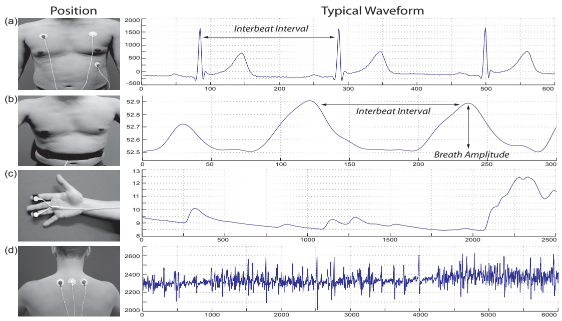

Figure 4: Position and typical waveforms of the biosensors: (a) ECG, (b) RSP, (c) SC, (d) EMG.

3.2 Feature Extraction

In offline condition, we have a variety of choices for applying signal analysis techniques to obtain relevant features. In the previous work (Kim and André, 2008), we proposed a wide range of physiological features from various analysis domains including time, frequency, entropy, geometric analysis, subband spectra, multiscale entropy, and HRV/BRV in order to search for the best emotionrelevant features. In the work, we achieved an average recognition accuracy of 95% from a naturalistic dataset obtained from a reliable experiment using a musical induction, which was not based on any lab setting or any deliberate instructions for evoking certain emotions. The recognition accuracy of 95% for four emotions (joy, anger, sadness, pleasure) connotes more than a prima facie evidence that there are some ANS differences among emotions.

For online systems, the choice of features is restricted to those that can be calculated possibly in realtime or near realtime at least. Therefore the effective use of feature selection and realtime signal processing techniques plays an important role. Based on the features in the previous work, we select diabetes-specific features for the IEM system.

3.3 Mapping Features with Emotions

In addition to the typical driving-relevant emotions such as anger, stress, anxiety, exciting etc., we classify physiological and behavioral symptoms of hypoglycemic events. Driving-relevant emotional states and hypoglycemic symptoms can be summarized as follows:

Driving-relevant emotions:

- Anger: leads to horn-honking, rapid steering and accelerating
- Stress (in multiple levels): related to traffic situation (e.g. rush hour) and other road user.
- Anxiety, calm, excitation etc.

Diabetes-specific emotions:

- Stress: blood sugar release is symptomatic of stress
- Fear of hypo-/hyperglycemia
- Depression: possibly because of imperfect relationship between self-care & health, or combination of acute & chronic stressors.
- Anger, nervous, anxiety

Signs of hypoglycemia:

- Mild: tremor, sweating, tachycardia, nervousness, heart palpitations, hunger
- Moderate: shaking, dizzy, headache, confusion, numbness of lips or extremities, cold, clammy skin, slurred speech, hyperventilation or shortness of breath
- Severe: disorientation, seizure, coma, unconscious

Based on these factors, we consider a novel emotion model combined with hypoglycemic symptoms (Figure 5) for the IEM system.

In addition to the statistical classifiers such as support vector machines, k-nearest neighbor, neural networks, etc. that are commonly used in pattern recognition, we develop a rule-based mapping method in which we generate rules for mapping particular features linearly to the change of certain emotional states. We employ this method especially for recognition of hypoglycemic symptoms, such as shaking, sweating, cold, tremor, rapid breathing and tachycardia, which can directly be detected by analyzing linear variation of related biosignals, for example, sweating by GSR, rapid breathing by RSP, tremor by EMG, etc. Therefore, the rule-based mapping algorithm can easily be implemented for realtime system without

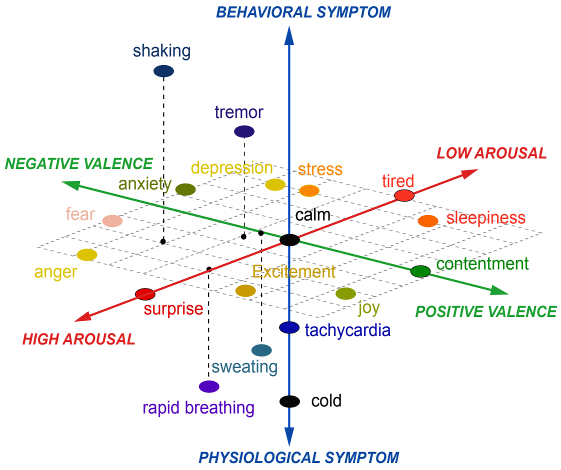

Figure 5: Discrete emotion model combined with hypoglycemia symptoms.

training a classifier. For the other emotions such as stress, joy, anger, and neutral, the recognition system needs to be learned from cross-correlated behavior of features from multichannel biosignals and requires a training dataset for supervised machine learning. As a result, we will need to develop a combined classification scheme of both rule-based mapping and supervised classification in order for recognizing multiple symptoms and emotional states. An ensemble method can also be considered for improved recognition accuracy, e.g. classifier ensemble method in which we classify by using different classifiers and combine the results from each classifier by using decision-level fusion algorithms such as majority voting, Borda count, and boosting.

Main challenge in the IEM system is overcoming possibly overlapping physiological reactions between hypoglycemic events and common emotional states and calibrating the biosensors in driving situation.

4 DISCUSSION: IMPACT OF EMOTIONS ON DIABETES (& VICE VERSA)

Patient's emotional needs and problems are an important component of treatment and integral component of diabetes management. The role of emotions in diabetes management was observed as early as the seventeenth century, when British physician Thomas Willis noted that diabetes first appeared among patients who had experienced significant life stresses.

Recently it is widely recognized that negative emotions such as stress, anxiety, fear, depression, and sorrow affect the blood glucose level (Surwit and Schneider, 1993). Patients experiencing such negative emotional states may have greater difficulty in controlling blood glucose compared to those not suffering emotional problems. Depression, for example, is not generally listed as complication of diabetes. However, it can be one of the most common and dangerous complications. More importantly, depression undermines the motivation of patient to maintain diabetic management. Diabetics with major depression have a very high rate of recurrent depressive episodes within the following five years (Lustman et al., 1997b). In the study of (Lustman et al., 1997a) it is proven that effective treatment of depression can improve diabetic control. Stress can also readily elevate blood glucose and affects the autonomic nervous system, which in turn affects the secretory rate of insulin and glucagon and finally disrupts metabolic control. Stabler and colleagues (Stabler et al., 1987) found that children judged to have a "Type A" personality structure had an increased blood glucose elevation in response to stress and children with a calmer disposition had a smaller glucose rise when stressed. Several studies have demonstrated a relationship of stress to glycemic control in samples of patients with Type 1 diabetes (Inui et al., 1998; Viner et al., 1996). Stress can be managed, for example, by using behavioral stress management program such as progressive muscle relaxation (PMR), or the administration of anxiolytic medications. Recently, the study in (Surwit et al., 2002) supported the efficacy of outpatient stress management training for the improvement of glycemic control in patients with Type 2 diabetes. For stress management training, they used the PMR and medication instruction methods complementarily. The result of their experiment showed that at the end of a 1-yea follow-up period, patients who received training in stress management skills demonstrated approximately a 0.5% reduction in HbA1c relative to control patients. While positive emotions such as laughter have been reported to modify the levels of neuroendocrine factors involved in negative emotions and to modulate immune function (Berk et al., 1989; Takahashi et al., 2001), less attention has been so far paid to impact of positive emotions on diabetes. Through the observation in (Hayashi et al., 2003) it is firstly elucidated that laughter can suppress the elevation of blood glucose level. From their 2-day experiment, it turned out that the patients with Type 2 diabetes had a smaller rise in post-meal blood glucose when they watched a comedy show than when they listened to a humorless lecture.

5 CONCLUSIONS

Research on the role of emotions in diabetes is still challenging work, because literature so far offers ideas rather than well-defined solutions. In this paper we presented conceptual scheme of in-vehicle emotion monitoring system for diabetic drivers. Many works remain to be done in the project METABO. To achieve our goals in this new area we conceived, it requires not only a methodological, technical innovation but also conceptual changes with workable thoughts focusing on specific contexts of medical applications.

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