Exploring Cognitive Distraction of Galvanic Skin Response while Driving: An Artificial Intelligence Modeling

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***Abstract*—It is quite often that we hear fatal traffic accidents due to driver's distraction. Car manufactures and researchers are therefore putting their efforts into car safety protection mechanism. However, the application of car safety protection mechanism is frequently hindered by its limitations, such as drivers' privacy or the high cost of its deployment and each of which leads to rare applications of car safety protection specifically in the field of non-autonomous cognitive distraction. This research proposal intends to apply the sensor of Galvanic Skin Response (GSR) to measure drivers' non-autonomous cognitive distraction due to the blood glucose variation of diabetes. SVM-RFE will be adopted as the major algorithm to create an alert mechanism with the artificial intelligence concept of supervised machine learning. The researched human-machine sense interaction mechanism can be able to embed into the car computer so that it can detect drivers' physiological changes during diabetes outbreak and then raise advisable alert and intervention accordingly.**

***Index Terms*—cognitive distraction, galvanic skin response, artificial intelligence, supervised machine learning**

I. Introduction

There are many companies in China devote in the development of unmanned vehicle, such as Baidu, Tencent and Alibaba [1]. These practitioners are undoubtedly wanting to commercialize their driverless technology as soon as possible to realize a better driving experience for humans. However, driverless technology needs to rely on many sensors to collect massive sensing data with extremely difficulty processing so that driverless technology can prevent traffic accidents that may occur during the driving process [2]. Goodrich & Schultz (2008) also asserted that "human-machine sensing interaction" will be the key factor that affects the success of unmanned driving technology [3], because whether or not the vehicle computer can seamlessly bridge the interaction between the driver and the vehicle should be vital to driverless technology.

A. Classification of Driving Distraction

According to the survey reported by National Highway Traffic Safety Administration that nearly 80% of traffic accidents were caused by driver distractions [4]. Azman *et al.* (2010) stated that driving distraction can be divided into three categories, including visual distraction, manual distraction and cognitive distraction [5]. Visual distraction represents the driver moves her/his eyesight from the road to somewhere (e.g., finding a parking place, checking a road sign), while manual distraction refers to the driver's hands leave away from the steering wheel and to do something (e.g., adjusting the seat, smoking). As for cognitive distraction, it means that the driver is mentally unable to focus on the driving task (e.g., communicating with passengers, thinking about something unrelated to the driving or physical discomfort).

B. Detection of Driving Distraction

Prior studies have figured out the way in which human-machine sensing interaction can be applied to protect driving safety when the driver has distractions. For example, Rongben *et al.* (2004) speculated the driver's cognitive distraction by using a camera to capture the driver's lip data and then applied neural network to model the driver's conversation or yawn [6]. Harada *et al.* (2014) elaborated the driver's visual distraction by using a camera to capture images of the driver's eye movements and also applied neural networks as the modeling algorithm [7]. Sathyanarayana *et al.* (2008) used a gravity accelerometer with a gyroscope to collect the driver's head and leg movements to determine if the driver has manual distraction [8]. Although these

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distraction detections are valid, they are practically inapplicable due to the facts that the driver's privacy can be violated by the detecting camera and the distraction detecting equipment can be cost a lot.

C. Lack of Detecting the Cognitive Distraction

It can be found that most of the detections about driving distraction focus on the type of visual distraction and manual distraction, however, the cognitive detection is rarely to be mentioned. Unfortunately, cognitive detection happened in various situations, including excessive drinking, fatigue driving and physical discomfort. When encountering these situations which are irresistible, the mechanism of early warning is necessary to prevent the car accidents caused by the cognitive distraction. Therefore, some researchers devote to the detection of cognitive distraction. Almahasneh *et al.* (2014) apply the Brainwave Scanner to collect ECG data from drivers, but the sensing equipment is heavy and expensive [9]. Dehzangi *et al.* (2018), however, applied Galvanic Skin Response (GSR) to overcome this research limitation [10]. GSR is an electrical skin conductivity sensor which collects data from the interaction between human psychological state (i.e., distraction) and her/his surrounding environment (i.e., driving). In addition, GSR uses patch to measure skin conductance and therefore it has relatively low deployment cost than other distraction detection equipment. Most importantly, the patch of GSR does not violate the subject's privacy in that it has no personally identifiable information. Nevertheless, the testing situation in his research is autonomous (talking on the phone or sending the message), so the result cannot be applied in the situations which are irresistible (physical discomfort or fatigue driving).

D. Difficult to Collect Data during Driving

There were few researchers applying the GSR device to detect the cognitive distraction, and the possible reason is that the variation of GSR data from human is really complicated. Furthermore, once researchers can explain the variation of GSR data, it can be used to identify the specific situations. However, it is trackable that the cognitive distraction is triggered by the physical discomfort from drivers. For example, a person who has the headache and loss the visual, it may triggered by the dropping of blood glucose. Therefore, if the driver with diabetes whose blood glucose rapidly change without the mechanism of early warning in the car, it may cause the serious car accident. Frier (2000) also verify that diabetic drivers may occur cognitive distraction due to the variation of the blood glucose [11]. However, with the limitation that the detection of blood glucose is invasive, it is difficult to collect data during the driving situation.

This research proposal applies GSR to evaluate the driver's cognitive distraction while driving. Specifically, drivers with diabetes will be selected as the research subjects to confirm whether or not their GSR values (physiological state) can be affected by the blood glucose variance. Evaluating cognitive distraction with diabetes drivers is quite different and rigorous than that of Dehzangi *et al.* (2018) even though their research mainly focuses on cognitive distraction as well [10]. As a result, drivers' irresistible distractions (e.g., distraction caused by disease attack) should be more harmful and unpredictable than autonomous distractions (e.g., using mobile phone). Therefore, the current research proposal combines the advantages of low cost, privacy protection, and practical feasibility to attempt to surpass the measurement obstacle of drivers' irresistible cognitive distractions in the past research.

II. Literature Review

A. Signals Detection Method from Human Body

Detecting the signals from human body is the foundation to understanding the various human reactions. There are many methods to detect the human signals, including ECG (Electrocardiography), EMG (Electromyography) and GSR (Galvanic Skin Response). ECG is a test that records the electrical activity of participant's ticker through small electrode patches that a technician attaches to the skin of his chest, arms, and legs. For example, Steinvil *et al.* (2011) applied ECG to collect data from athletes in the break time and exercise time separately, aiming to explore whether the detection of ECG can reduce the possibility of sudden cardiac death in athletes [12]. However, due to ECG is a multiple-point detection, it is not suitable for the driving situations (e.g. ankles sensing may affect the driving safety). As for the EMG detection, it is diagnostic procedure to assess the health of muscles and the nerve cells that control the motor neurons. For its practical application, Donovan *et al.* (2015) applied the EMG to explore the muscle status from the participant who has Chronic Ankle Instability during his/her exercise time [13]. However, EMG is not a suitable method to detect the cognitive distraction during driving situation because of its invasive detection may cause uncomfortable feeling for drivers. Last but not least, GSR detection refers to the changes in sweat gland activity which are reflective of the intensity of participants' emotional state. Horvath (1978) proposed that human skin is a conductor, so that can judge the physiological (GSR data) and psychological (feeling happy or sad) reaction of participant by the variation of sweat secretion [14]. However, GSR data is variety of variation, so it is difficult to define how specific waveform of GSR data can correspond to the specific psychological reaction.

Due to the low cost and convenient usage [10], we attempt to apply GSR as the method to collect data from drivers, besides, we can embed the GSR device into the steering wheel, so that can reduce the Hawthorne Effect. After that, we try to define the specific GSR data by supervised machine learning, so that can correspond to the specific psychological reaction.

B. The Applications of GSR

Due to the low cost and the convenient usage of the GSR, researchers applied it as the method to collect data in many different applications. It can roughly classify the application fields of GSR into the psychological status

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mining and the physiological status confirmation. For the application of the psychological status mining (explore the psychological status from the participant), Kurniawan (2013) detect stress from speakers with the signals of GSR data, aiming to provide the better stress management [15]. For the application of the physiological status confirmation, Majumder (2017) considered that sensors paly the key role in the smart home [16]. In order to know the activity of elders at home and ensure their safety, it can be realized with the wearable device embedded the GSR sensor.

In this study, we attempt to across the applications between the psychological status mining and physiological status confirmation. We collect the GSR data to detect the psychological status from drivers during the driving situation, then modeling for the identification of the cognitive distraction caused by their physical discomfort according to the GSR data.

III. Research Method

There are five steps in our research method (Fig. 1), including raw data collection, data classification, data segmentation and analysis, features extraction, features selection and modeling.

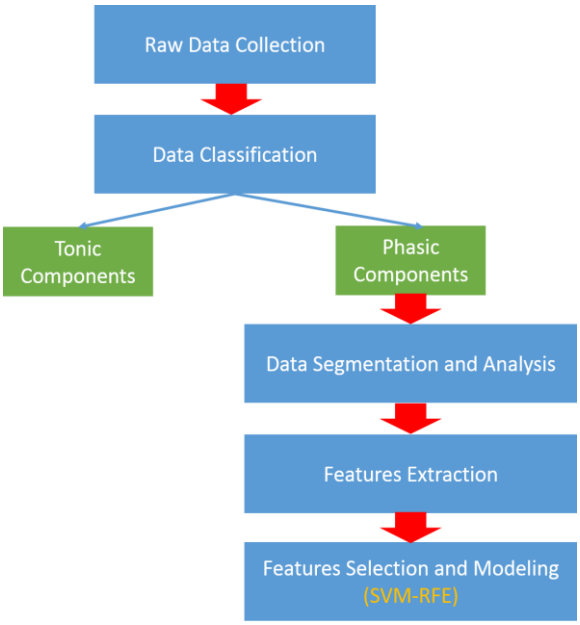

Figure 1. The research steps

A. Raw Data Collection

1) Participants and conditions

In order to detect the occurrence of the irresistible cognitive distraction from drivers, we select four diabetic patients as the participants in this study. The main reason is that diabetes is a chronic disease and patients' blood glucose fluctuation may affect their driving safety [17]. With the trend of the age about the diabetic patients becomes younger [18] and the average age is 59.9 [19], we select the participants in male between the age of 30-40. Besides, we start to collect GSR data from drivers as a dinner time approached, aiming to capture the process that blood glucose declines. Finally, in order to identify the occurrence of the cognitive distraction by the supervised machine learning, we treat four diabetic patients as experimental groups, and also select four healthy people as the control group.

2) Deplyment of GSR decive

In this study, we drive the GSR sensor by Arduino, a single-chip microcomputer. Arduino is famous for Makers recently, and users can control their sensors with its exclusive Integrated Development Environment (IDE). GSR is a wearable device (Fig. 2 [20]), it is composed by a digital to analog converter and two finger sleeves with electrode. Besides, we attempt to embed the GSR device into the steering wheel to reduce the Hawthorne Effect, so that can realize the data collection only by holding the steering wheel for participants.

Figure 2. GSR device [20]

B. Data Classification

The collected data will divide into two types, including tonic components and phasic components. The former represents a long-term skin conductance whereas the latter refers to short-term skin conductance. In this study, due to the occurrence of the cognitive distraction belongs to the specific events arising the variation of the skin conduction, we only select phasic components as the modeling target afterwards.

C. Data Segmentation and Analysis

With the characteristic that phasic components varies with time and affected by multiple factors, we adopt Spectral Analysis to evaluate its features. In order to explore the time-frequency features from the experimental group (diabetic patients) and control group (healthy drivers) based on the phasic components, we adopt Time-Frequency Analysis to analyze the spectral and temporal distribution. Dehzangi *et al.* (2018) also used the method stated above to analyze the phasic components in three different situations [10], including the general driving situation, driving situation with talking on the phone and driving situation with sending the message. The outcome is shown in Fig. 3 below.

Besides, in order to enable data responds in the short time, we adopt the method of sliding windows to segment data. Each windows include 5 seconds, and we extract the fifth data by superimposing four data in the front.

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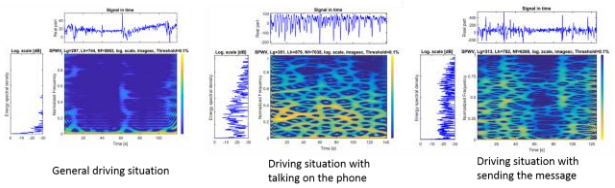

Figure 3. Output of the time-frequency analysis

D. Features Distraction

In each window we will extract eight features for machine learning afterwards, including Average, Variance, Accumulation, Maximum, Minimum, Peak number, Average of peak's aptitude and Auto-regression. They are listed below as Table I.

TABLE I. LIST OF FEATURES

Feature Name	Feature Description
Average	the average of the phasic components in a window
Variance	the average distance between each sample points and Average in a window
Accumulation	Sum of the phasic components in a window
Maximum	The maximum value of phasic components in a window
Minimum	The minimum value of phasic components in a window
Peak number	If both side of value less than the current value, counted as a peak
Average of peak's aptitude	The average of the peak's aptitude in a window
Auto-regression	An output by an AR model based on the data in a window

E. Features Selection and Modeling

In this study, we will apply SVM-RFE (Support Vector Machine-Recursive Feature Elimination) to select the features. First, it will classify the data into two groups according to the given features with SVM algorithm, then the features will be sorted by the received score. Next, the feature with lowest score will be eliminated, and the remaining features will continue to train the model. After several iterations, we finally select three target features for modeling and achieve the purpose of identifying the cognitive distraction in a high accuracy.

IV. EXPECTED RESULTS

With skin conductance sensing and machine learning, the current study is expected to be able to detect the decline of blood glucose in diabetes sufferers during their driving. This will not only solve the detection problem of diabetes drivers while driving, but also practically contribute to an artificial intelligence warning mechanism that reduces traffic accidents when the drivers come across to irresistible distraction. More specifically, the expected results of this study include: (1) confirming the GSR difference between healthy and diabetes drivers. (2) Applying GSR to the driving scenario of irresistible distraction. (3) Creating artificial intelligence machine learning model in the field of driverless technology. (4) Specifying cognitive distraction measurement in both academy and practice.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

All the authors have contributed to this study equally.

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