Revealing driver psychophysiological response to emergency braking in distracted driving based on field experiments

Ying Li
School of Information Engineering, Chang'an University, Xi'an, China

Li Zhao
Nebraska Transportation Center, University of Nebraska-Lincoln, Lincoln, Nebraska, USA

Kun Gao
Department of Architecture and Civil Engineering, Chalmers University of Technology, Gothenburg, Sweden

Yisheng An
School of Information Engineering, Chang'an University, Xi'an, China, and

Jelena Andric
Volvo Group Trucks Technology, Gothenburg, Sweden

Abstract

Purpose – The purpose of this paper is to characterize distracted driving by quantifying the response time and response intensity to an emergency stop using the driver's physiological states.

Design/methodology/approach – Field tests with 17 participants were conducted in the connected and automated vehicle test field. All participants were required to prioritize their primary driving tasks while a secondary nondriving task was asked to be executed. Demographic data, vehicle trajectory data and various physiological data were recorded through a biosignalsplux signal data acquisition toolkit, such as electrocardiograph for heart rate, electromyography for muscle strength, electrodermal activity for skin conductance and force-sensing resistor for braking pressure.

Findings – This study quantified the psychophysiological responses of the driver who returns to the primary driving task from the secondary nondriving task when an emergency occurs. The results provided a prototype analysis of the time required for making a decision in the context of advanced driver assistance systems or for rebuilding the situational awareness in future automated vehicles when a driver's take-over maneuver is needed.

Originality/value – The hypothesis is that the secondary task will result in a higher mental workload and a prolonged reaction time. Therefore, the driver states in distracted driving are significantly different than in regular driving, the physiological signal improves measuring the brake response time and distraction levels and brake intensity can be expressed as functions of driver demographics. To the best of the authors' knowledge, this is the first study using psychophysiological measures to quantify a driver's response to an emergency stop during distracted driving.

Keywords Mobile phones, Driver distraction, Emergency braking, Psychophysiological, Response time, Psychophysiological measure

Paper type Research paper

1. Introduction

According to the National Bureau of Statistics of China (NBSC), approximately 61,703 Chinese were killed in automobile accidents in 2020, and more than 90% of those accidents were caused by human errors (NBSC, National Bureau of Statistics of China, 2021). To this end, advanced driver assistance systems (ADAS) are developed to prevent many human errors causing accidents during the driving process for safety and better driving (Mishra and Kumar, 2021). United States National Highway Traffic Safety Administration reported that distracted driving caused 3,142 lives lost in motor vehicle

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crashes in 2020 nationwide in the USA (NHTSA, the National Highway Traffic Safety Administration, 2019). Distracted driving refers to any activities that could divert a motorist's attention away from the primary task of safe driving. It has been widely acknowledged as a risky behavior that poses a danger to the vehicle occupants and the traffic community (e.g. motorists, pedestrians and bicyclists). Distractions in driving can be generally categorized into three types:

1 visual, e.g. looking at something other than the road;
2 manual, e.g. manipulating something other than the steering wheel; and
3 cognitive, e.g. thinking about something other than driving.

In the actual driving context, the distraction sources are usually complex and may include a combination of one or more of the three types. The most alarming facts are that the driver's visual, manual and cognitive attention are often altogether distracted away from driving, such as texting or playing mobile games (AAA Foundation for Traffic Safety, 2020). Therefore, it has been attracting a large body of research attention to underline how drivers react when driving with multiple distractions (Qi *et al.*, 2020).

Several studies have reported that distractions cause brake response, especially when braking is urgently needed (Lee *et al.*, 2001; Strayer and Johnston, 2001; NSC, the National Safety Council, 2012; Gao and Davis, 2017). Brake response time is one of the critical surrogate measures for crash risks (Green, 2000; Jurecki and Stanczyk, 2014). The brake response time can be typically obtained by observing the brake lights (Johansson and Rumar, 1971) or measuring the pedal effort (Fitch *et al.*, 2010; Gao and Davis, 2017). In the literature, braking response time varies due to driver's expectations (Green, 2000), level of attention (Lee *et al.*, 2001), situation urgency (Summala, 2000), as well as differences in measuring methods (Jurecki and Stanczyk, 2011). However, these previous studies designed driving tasks and traffic scenarios without sufficient concern for the driver's psychophysiological response to emergency braking.

Conventional ADAS use automated technology to detect nearby obstacles or driver errors, which relies on inputs from multiple data sources, including automotive imaging, lidar, radar, image processing and computer vision. Human cognition is a critical factor for traffic accidents and poor driving performance, assessment of covert cognitive states of drivers through psychophysiological measurements is adopted by ADAS to predict and augment risky driving behavior (Lohani *et al.*, 2019). With the rapid growth of sensor technology, researchers began to investigate the behavior of distracted driving with psychophysiological signals such as heart rate, breathing, blood pressure and skin conductance (Grassmann *et al.*, 2016; Haufe *et al.*, 2014). Currently, it has been widely used for investigating drivers' fatigue and drowsiness (Li *et al.*, 2011), distraction and inattention, mood (Castegnetti *et al.*, 2017) and aggressiveness (Malta *et al.*, 2001). Unsurprisingly, it also shows an innovative way to measure drivers' brake response time during distractions (Arakawa *et al.*, 2019; Gao *et al.*, 2020).

Past studies associated with measuring the impact of distracted driving on safety can be categorized into three types, including data analysis (Peng and Boyle, 2012; Qin *et al.*, 2019; Jamil *et al.*, 2021), driving simulator studies (Nowosielski *et al.*, 2018; Xu and Lin, 2018; Arkonac *et al.*, 2019; Zhang *et al.*, 2019; Baldo *et al.*, 2020) and field studies (Dingus *et al.*, 2016; Ma *et al.*, 2018; Arvin *et al.*, 2019; Hernández-Rojas *et al.*, 2019; Arvin and Khattak, 2020; Gao *et al.*, 2021). Due to driving simulation providing a low-cost method for driver behavior data collection, most distracted driving studies were conducted in a simulator environment. Field study is undertaken within a natural environment, allowing researchers to gain firsthand experience and knowledge about the people, events and processes they study. However, the acquisition of field data is costly and time-consuming. Compared with data analysis and driving simulator study, the field study is a more appropriate approach to quantifying distracted driving behaviors and their influences on other factors (Wu and Xu, 2018; Wijayaratna *et al.*, 2019). Currently, there are few reports of studies related to secondary in-car tasks. Most field studies investigate the naturalistic driving data collected from the cameras and sensors to find the riskiest factors outside the vehicles faced by drivers during driving (Dingus *et al.*, 2016; Arvin and Khattak, 2020). There is still a lack of field tests of drivers' physiological states of driver distraction involves a secondary task when an emergency brake occurs.

Drivers with experience in using ADAS on more vehicle control tasks, like adaptive cruise control and lane-keeping assist, may increase drivers' engagement in distracted driving (Arkonac *et al.*, 2019; Hungund *et al.*, 2021; Xue *et al.*, 2021). With the developments in the field of wearable physiological sensors (Lu *et al.*, 2020), the additional information collected from the driver will be used to improve the ADAS. This study attempted to outline an explanatory framework for emergency brakes in distracted driving situations, characterized by driver demographics, vehicle kinematics and more importantly physiological signals. Using a biosignalsplux signal data acquisition toolkit, an experiment was properly designed to characterize distracted driving related to secondary in-car tasks by quantifying the response time and response intensity to an emergency stop using the driver's physiological states. Specifically, the paper attempts to answer the question when the driver of a vehicle is suddenly faced with a critical risk of collision, how fast and strong an evasive maneuver (e.g. brake) is applied given the driver is distracted driving. The proposed framework will guide the potential causal role of distraction load when drivers use ADAS.

2. Experiment setup and testing field

The test field is located at the automobile test ring road of Chang'an University in Xi'an, China. This oval-shaped, closed test ring road measures 2.4 km long in total, complemented by a 1.1 km straight road on its central axis. The experiments were conducted at the northeast corner of the test field where parts of the ring road and the straight road form a loop, as indicated in Figure 1. The test vehicle is a compact SUV manufactured by BYD auto group in China. The vehicle model is BYD Yuan EV360 with front-wheel drive and automatic transmission. It should be noted that the test vehicle is electric-powered, and electric vehicles' driver behavior patterns will be different from those of traditional gasoline vehicles. There are some

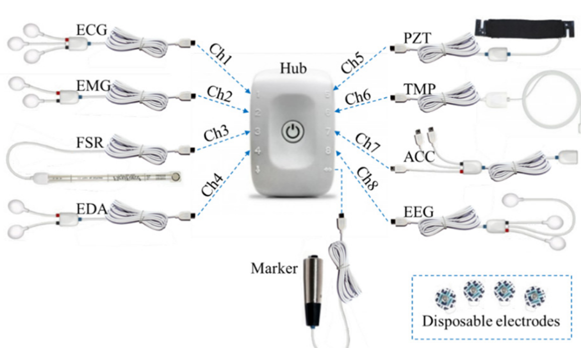
Figure 1 The test site at Chang'an University

differences in driving characteristics between electric vehicles and gasoline vehicles, particularly a stronger accelerating and decelerating within the first experiences with electric vehicles (Helmbrecht *et al.*, 2014).

During the experiments, the focus is on using advanced measurement devices to collect data about the driver's physiological states. Biosignalsplux, a body sensor system from Plux^{TM}, Portugal, is adopted in this study. It provides solutions to acquire reliable psychophysiological signal data by integrating various user-selectable sensors, working with Bluetooth and internal memory. Because of its low-cost, purpose-built and self-wearable, the toolkit is ideal for field driving tests. Figure 2 shows the Biosignalsplux signal data acquisition toolkit used in this study. An eight-channel wearable hub is plugged into eight amplifiers (i.e. body sensors), and their succinct applications are listed below:

1 *Channel 1*: Electrocardiography (ECG) for heart activity;
2 *Channel 2*: Electromyography (EMG) for muscle activity (e.g. the right calf);
3 Channel 3: Force-sensing resistor (FSR) for braking force;
4 *Channel 4*: Electrodermal activity (EDA) for skin conductance;
5 *Channel 5*: Piezoelectric respiration (PZT) for respiration change;
6 *Channel 6*: Temperature (TMP) for body surface temperature;

Figure 2 Biosignalsplux data acquisition system



7 *Channel 7*: Accelerometer (ACC) for vehicle braking deceleration rate; and
8 Channel 8: Electroencephalography (EEG) for brain activity.

Body sensors (i.e. ECG, EMG, EDA and EEG) used pregelled (coated with Ag/AgCl polymer and conductive/adhesive hydrogel), disposable, snap-on electrode patches. As shown in Figure 2, these peel-and-stick disposable electrodes are buckled onto the sensor heads and attached to the corresponding skin surface of the human body. In addition to the eight-channel sensors, the system also includes a marker (see Figure 2), which is a handheld switch for event annotation. In the time-stamped data recording, the period of a certain event can be marked by continuously pressing or releasing the button (pressing = 1, releasing = 0). It facilitates locating the event in later data review or processing without affecting the functionality of the system. The system comes with software that is a suite of data analysis add-ons for real-time signal visualization and recording. Data are acquired from all channels simultaneously and transmitted to the local server (e.g. laptop) wirelessly.

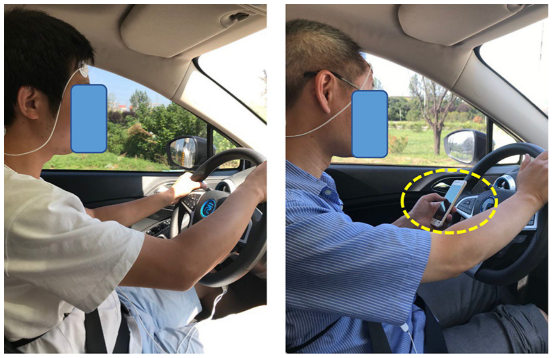
The experiments were conducted from 19 to 26 August 2019. Because the test field was closed (nonpublic), no pedestrians or other vehicles would be present on the test track. At the beginning of the experiment, all the drivers wore the toolkit of the body sensors by professional staff to ensure the correct setup. Afterward, the divers were required to drive the vehicle on the test loop and execute different driving tasks. During driving, the participants were asked to perform three hard braking maneuvers in response to a clear verbal "stop" order given by the experiment assistant in the car. The "stop" order was randomly given when vehicles were running on a straight section of the test site. The time gap between any two "stop" orders was greater than 1 minute to avoid confound effects.

In the worst-case scenario where drivers are distracted in all three ways – visual, manual and cognitive, a secondary task of playing a game on a mobile phone was designed. That said, two driving scenarios were tested for each participant:

1 regular driving when safe driving is the primary and only task of the participant; and
2 distracted driving where drivers are asked to execute a secondary nondriving task (mobile game) under the premise of safe driving.

Figure 3 shows the status of the participants in the two driving scenarios during the test. The source of driving distraction is designed to play a coloring game. In the game, a simple picture of seven colors is pixelated into 618 equal cells. Participants can color it by numbers (1 through 7 correspond to seven given colors) marked in the cell. Participants were told that the final game score consisted of gaining points for correct coloring and double losing points for incorrect coloring, and a higher score would be rewarded. The participants must pay enough attention to their mobile phones to handle the game properly. In contrast to regular driving, participants' visual, manual and cognitive abilities would be affected to varying degrees by distracted driving. Specifically, the participant's vision must switch back and forth between the road and the mobile screen; the participant holds the mobile phone with one hand which is

Figure 3 Regular driving (left) and distracted driving (right) in the test



off the steering wheel; and the participant allocates some cognition to the mobile game.

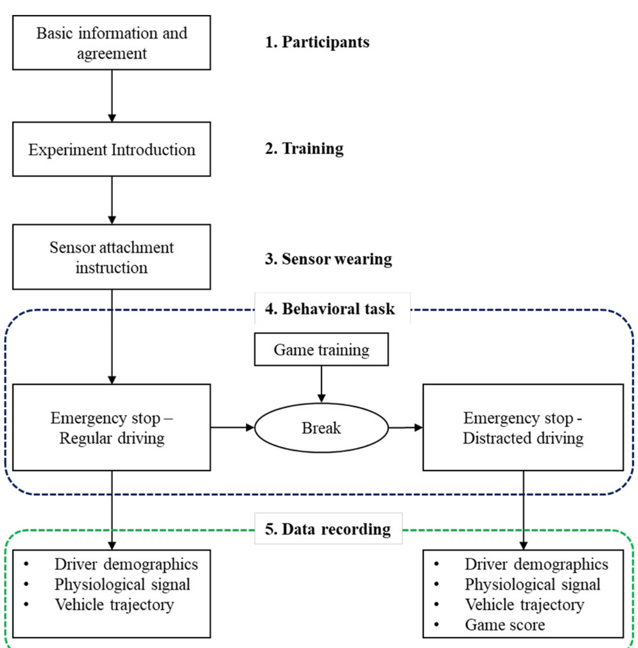
3. Experiment process and data collection

3. 1 Experiment process

According to the experiment design in this study, the data acquisition procedure mainly includes five steps, as illustrated in Figure 4. Each step is elaborated on below.

First, the introductions about the experiments were provided to participants including showing the test site and getting familiar with the test vehicle. Participants were told that the upper-speed limit of the test site was 40 km/h, but they can drive at their self-evaluated safe speed. For example, they may slow down when they are in uncertain driving conditions, limited sight distance or distracted. Besides the driving task, all participants were told that an emergency stop order would be randomly released by the assistant sitting next to them, and that they should act immediately once heard. The experiment lasts about 30 minutes for each participant.

Figure 4 Data acquisition procedure



Next, the experimental staff attached the electrodes of four sensors onto the corresponding locations of the participant's bodies. More specifically, the three-lead ECG (for heart activity) was attached to the participant's left chests. EMG for muscle activity during braking was measured with three electrodes, two positioned at the right calf muscles and one stuck to the right ankle (less muscle) as the benchmark. EDA for skin conductance attached two electrodes to the sole of the foot (mostly left foot). EEG (for brain activity) had three electrodes: one long electrode was stuck onto the forehead while the other short electrodes were on the back of the head. The technical details about obtaining physiological signal data from the equipment are available in PLUX (2019) and Braithwaite *et al.* (2013). The PZT sensor for respiration was tied to the participant's chest by an elastic strap. A localized sensing element was embedded to measure displacement variations due to inhaling or exhaling. Moreover, TMP was used for skin temperature with only one contact thermistor taped to the skin surface of the leg. Another two sensors are not on the driver. The FSR sensor was taped onto the center of the braking pedal to measure the braking force. The ACC sensor was firmly taped on the vehicle to measure the deceleration on the longitudinal of the vehicle.

In regular and distracted driving situations, participants were asked to take an emergency stop. Specifically, participants randomly received a verbal "stop" order from the experiment assistant in the vehicle. After receiving the order, the participants must brake to a complete stop. The participants were told that this "stop" order was to mimic emergency braking scenarios such as a sudden jaywalker cutting in front or almost hitting another car. The urgent and compact "stop" order forced drivers to brake to the best of their ability as soon as possible. A break of approximately 5 minutes was designed between the tests of the two driving situations to eliminate successive effects.

3.2 Participants

As listed in Table 1, 17 participants between the age of 20 and 59 who hold a license ranging from less than 1 year to 20 years were recruited. The participants come from different occupational backgrounds and are overall in good health status (e.g. free from drowsiness, illness and drunkenness). Prior to the experiment, verbal consent for voluntary participation was received from all participants. The basic information of the participants including age, gender, driving experience and education level (e.g. high school degree, university degree and graduate degree) was collected as well. After the experiment, each participant was compensated 50 RMB for their participations. The 17 participants include 3 females and 14 males, with the educational attainments ranging from middle school to PhD degree. The average age was 33.2 years with a standard deviation (SD) of 10.8 and the average license-hold was 7.8 years with a SD of 7.1. The mean driving experience is 6.4 years with a SD of 7.6. To be more generally representative, the experiment attempted to balance the demographics of the participant samples as much as possible.

3.3 Data collection

The collected data during the experiments mainly include the eight-channel physiological signals (i.e. ECG, EMG, FSR,

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Table 1 Driver demographics summary

Driver ID	Gender	Educational attainment	Age	License-hold year	Estimated actual driving year
1	Female	> bachelor's degree	33	9	2
2	Female	> bachelor's degree	32	5	5
3	Female	> bachelor's degree	37	0.5	0.1
4	Male	≤ bachelor's degree	40	7	5
5	Male	≤ bachelor's degree	37	4	4
6	Male	> bachelor's degree	51	18	18
7	Male	≤ bachelor's degree	59	22	22
8	Male	> bachelor's degree	24	6	1
9	Male	> bachelor's degree	45	20	20
10	Male	≤ bachelor's degree	36	17	17
11	Male	≤ bachelor's degree	24	5	5
12	Male	> bachelor's degree	25	4	1
13	Male	> bachelor's degree	25	0.1	0.1
14	Male	> bachelor's degree	24	4	2
15	Male	> bachelor's degree	29	7	4
16	Male	> bachelor's degree	24	3	3
17	Male	≤ bachelor's degree	20	0.3	0.1

EDA, PZT, TEP, ACC and EEG). The characteristic parameters were mainly focused on time-domain features (e.g. the response of the signal) and intensity-domain features (e.g. the amplitude of the signal). Note that the only difference of data recording between the two driving situations (regular vs distracted driving) is the need to save the game results for the distracted driving. The data acquisition system is set with a resolution of 16 bits and a sampling rate of 1,000 Hz for all channels. In addition, the vehicle trajectory, including latitude, longitude, instantaneous speed and time stamps, were also recorded every 0.1 seconds using a GPS mobile application software. Physiological signal and vehicle trajectory data were synchronized in time series.

4. Data process and analysis methods

4.1 Vehicular speed profiles

The speed profile data (SPD) before and after the "stop" order (i.e. stimuli) were extracted from the originally recorded vehicle trajectory data set. The timestamp when the stop order is issued is set to zero (i.e. benchmark), and the time prior to the stop event is labeled as negative. As shown in Figure 5, the trajectory data of all stop events are normalized, in time, so that all speed profiles are in a time window of negative 4–7 seconds.

Three parameters were used to characterize the SPD:

1 initial speed, obtained by averaging the speeds prior to the event (i.e. $t < 0$ in Figure 5);
2 deceleration rate, obtained by calculating the slope of the linear part of the speed reduction; and
3 reaction time, obtained by measuring the duration from the start of the event (t = 0) to the time when the speed reduced to 10% of the initial speed.

SPD of the first three participants is not included as partial data of the three participants are missing. For the sake of robustness, the full data from 14 participants are analyzed.

4.2 Physiological signal data

Figure 6 provides examples of different physiological signal data in the regular driving (in grey) and distracted driving (in

Figure 5 Examples of vehicle speed profiles for each participant

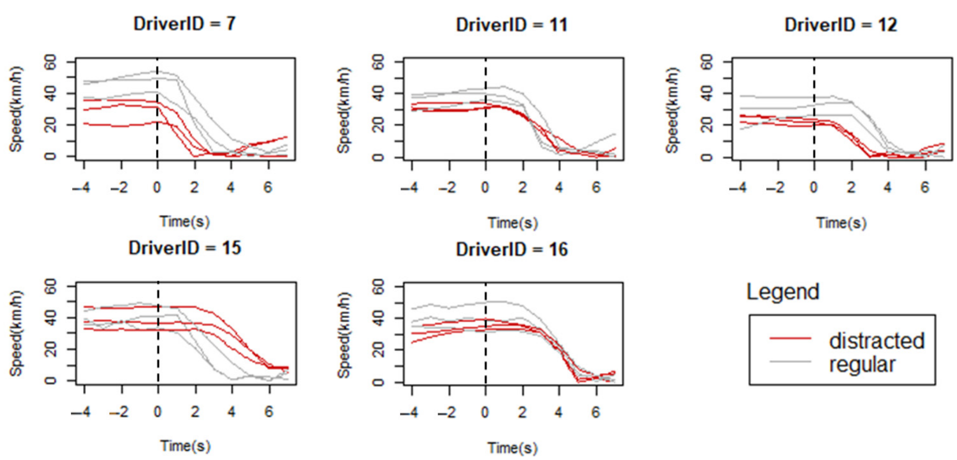
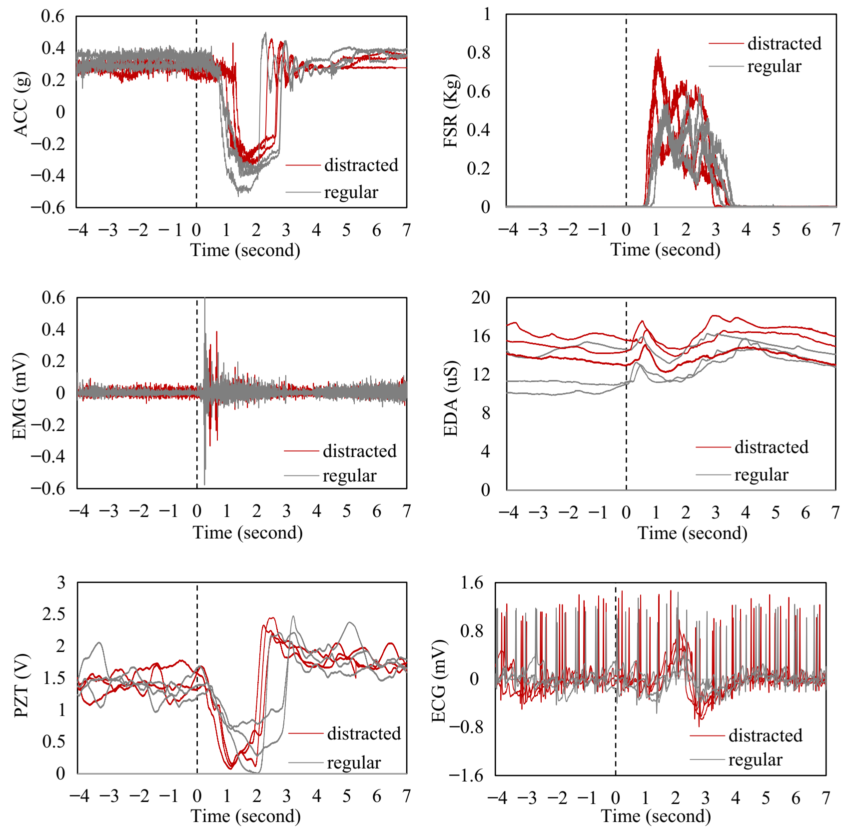


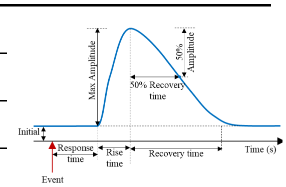
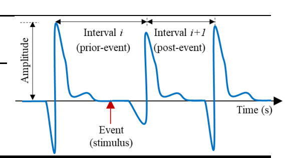
Figure 6 Physiological signal data in distracted and regular driving situations (Driver ID = 13)



red) situations. By manually checking the pattern of the data, TMP and EEG signal data were not distinctive or informative parameters. Therefore, these two signals were not interpreted in the following study.

As shown in Figure 6, each profile represents a signal data change over time prior to and post to a stop event. Each participant received at least three "stop" orders in each driving situation. The average performance of the "stop" even was used for analysis to reduce the random error. Figure 7 summarizes the characteristics of each physiological signal. The parameters to characterize different physiological signals are related to the amplitude and time of critical changes. The unit of amplitude corresponds to each physiological signal and the units of all time-related parameters (e.g. timestamp, duration and interval) are in seconds. These parameters can be either extracted directly from the signal data, as illustrated in the last column of Figure 7, or calculated from the parameters obtained. A preliminary data cleaning process was conducted to delete

Figure 7 Characteristic parameters of each physiological signal

Signal	Unit	Prior-event parameters	Post-event parameters	Parameter illustration
ACC	*g**	initial acceleration	max amp., response time, recovery time	
FSR	*Kg*	-	max amp., response time, rise time, recovery time	
EMG	*mV*	-	max amp., time at max amp., response time	
EDA	*uS*	initial skin conductance level	max amp., response time, rise time, 50% recovery time	
PZT	*V*	Initial respiration	breath-to-breath intervals, amp. of each breath	
ECG	*mV*	beat-to-beat intervals	beat-to-beat intervals	

Note: *The data acquisition system reports acceleration in the unit of *g*, 1 *g* = 9.81 m/s^2

some outliers or incomplete data. For example, the electrode of a specific sensor may be off from the participant accidentally during the test, resulting in no change or illegible change in the obtained signal data. Those signal data were excluded from the analysis result presented in Section 4.3.

4.3 Second-task performances

The participants' distraction level is quantified by their completion degree of the designed mobile game. In other words, it is hypothesized that the better the game is completed, the higher the mental load is required, and thus the higher the distraction level is reached. Conversely, it is hypothesized that a worse game completion refers to a lower distraction level, as participants assign more attention to the primary driving task rather than the secondary nondriving task (i.e. mobile game). Examples of game snapshots in low, medium and high distraction levels are shown in Figure 8. The game score is calculated from the "gain-points" and "lose-points" for each participant. With a total of 618 digital pixel cells in each snapshot in Figure 8, the gain point is counted when a cell is correctly colored, while incorrect coloring results in double lose points. The scoring rate (SR) is calculated as the quotient of the total scores and the game duration is adopted to measure the game scoring performance, as shown in Table 2.

In Table 2, the distraction SR of 16 participants is investigated considering different durations of the finishing game (due to the lack of data, participant Driver ID = 3 was not included). The scoring rate is divided into three levels to reflect the distraction load of a driver: low ($SR \leq 0.5$), medium ($0.5 \leq SR < 1$) and high ($SR > 1$).

5. Results and discussions

5.1 Speed profile analysis result

The results of the speed profile data analysis are summarized in Table 3. It was found that, on average, the initial speed of distracted driving (31 km/h) is lower than the initial speed of regular driving (36.5 km/h), and the difference is significant ($p = 0.002$). This was not surprising, in the literature, distracted drivers have been repeatedly reported to compensate for the risk of distraction by reducing their driving speeds (Caird *et al.*, 2008). The difference in average deceleration rate for the two driving situations was also significant ($p = 0.004$), noting that a harder brake was taken when an emergency "stop" was

Figure 8 Snapshots of driver's digital coloring task indicating high (left), medium (middle) and low (right) for Driver ID = 1, 8 and 11, respectively

Table 2 Distraction load summary

Driver ID	Duration (s)	Gain (pts)	Lose (pts)	Total scoring rate *SR* (pts/s)	Distraction load level
1	272	341	8	1.19	high
2	310	361	8	1.11	high
4	292	159	7	0.49	low
5	274	324	3	1.16	high
6	196	249	10	1.17	high
7	326	152	21	0.34	low
8	187	141	4	0.71	medium
9	176	239	1	1.35	high
10	354	269	12	0.69	medium
11	260	60	19	0.08	low
12	219	177	1	0.80	medium
13	338	247	8	0.68	medium
14	250	273	13	0.99	medium
15	261	159	10	0.53	medium
16	202	254	12	1.14	high
17	365	154	11	0.36	low

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Table 3 Characteristic parameters of SPD

	Initial speed (km/h)		Avg. deceleration rate (m/s^2)		Response time (s)	
Driver ID	**Distracted**	**Regular**	**Distracted**	**Regular**	**Distracted**	**Regular**
4	34.8	40.3	−2.80	−3.24	1.3	2.4
5	36.3	44.6	−1.54	−3.34	2	2.9
6	33.9	32.7	−1.77	−3.26	2.1	1.1
7	29.0	48.0	−0.83	−3.17	1	0.3
8	27.7	34.1	−2.02	−2.07	2.1	1.4
9	36.5	38.5	−3.79	−2.59	1	1.4
10	28.4	29.6	−2.25	−2.83	1.4	1.1
11	32.1	39.8	−2.79	−4.25	1.8	1.5
12	22.0	32.2	−1.71	−3.36	2.2	1.1
13	27.9	30.3	−2.14	−2.24	2.6	2
14	27.8	34.9	−2.19	−2.93	1.4	2.2
15	38.3	40.6	−1.44	−3.23	1.2	3.1
16	36.0	40.1	−1.83	−2.44	2.6	2.7
17	23.9	24.6	−2.22	−2.42	2.6	1.5
Avg.	31.0	36.5	−2.09	−2.96	1.81	1.76
Std.	5.1	6.3	0.71	0.57	0.59	0.81
***P*–value**	0.002*		0.004*		0.866	

Note: *Means significance at the confidence level of 99%

required in regular driving (avg. deceleration = $-2.96\,\mathrm{m/s^2}$) as compared to the distracted driving (avg. deceleration = $-2.09\,\mathrm{m/s^2}$). This may indicate the distracted drivers did not fully brake. The study hypothesized that distracted drivers take a longer time on average to respond to the "stop" order. However, it was not confirmed statistically in the data. It should be noted that due to the inherent accuracy of this method, the reaction time obtained by the SPD may not necessarily reflect the actual difference. The following physiological data may provide a better solution to this problem.

5.2 Physiological factor analysis and results

Table 4 provides the statistics of the physiological signal data (i.e. FSR, ACC, EMG, PZT, ECG, ECG and EDA), including the average values and the standard deviations in the parentheses. A paired two-tailed *t*-test with a *p*-value is performed to test if there are significant differences in the investigated indicators between distracted and regular driving. The *p*-value is marked in bold red when the test is rejected at the confidence level of 0.05, and in bold black when the *p*-value is marginally significant (at the confidence level of 0.1).

5.2.1 Kinematic signals – accelerometer and force-sensing resistor

In Table 4 (1), ACC data find two significant parameters, namely the maximum amplitude of the deceleration and the rise time in distracted driving. These two parameters correspond to the significance of the average deceleration rate. As for the response time, there was no significant evidence found in ACC signal data. In Table 4 (2), the intensity of the brake force, extracted from the FSR signal, is prominent with an average maximum of 0.297 and 0.262 kg for distracted driving and regular driving, respectively. Three key periods: response time, rise time and recovery time, were measured and the rise time was found significant in distracted driving as compared to regular driving (p = 0.006). Although the amplitude of the FSR may be remarkable for the intensity of the response, it is not significant (p = 0.542). This is because the sensor head attached to the brake pedal is tiny and thin, so it is easy to miss the partial braking force of the foot on the pedal. It is found in the FSR data that the amplitudes differ greatly from each other. To interpret the kinematics of the vehicle, distracted drivers tend to respond slower, pressed the brakes harder and had shorter times to maximum brake pedal depression than regular drivers. This may partially be because distracted drivers who immediately return to execute the stop maneuver, are not quite sure about the external condition and thus drivers are not able to sharply brake.

5.2.2 Physiological signals – electromyography and electrodermal activity

Evidence can also be found from the EMG signal data in Table 4 (3) to indicate the significance of the rise time in distracted driving (p = 0.027). EMG finds marginal evidence for the significance of the response time (p = 0.057). Therefore, detecting the physiological signal of the calf muscles during braking is more powerful than catching the force applied on the brake pedal (i.e. FSR) to distinguish between distracted driving and regular driving. It can be found in Table 4 (4) that, on average, the initial EDA level of distracted drivers is significantly higher than that of regular drivers (*p*-value = 0.005). When the event of an emergency stop is activated, skin conductance responds to it clearly, a drastic increase of the max amplitude of the skin conductance (i.e. the third column vs the second column) is observed. There may be marginal evidence for the difference in skin conductance response time (p = 0.070) and rise time (p = 0.067), indicating that the distracted driver may take longer time to react to the emergency stop than the regular drivers. The current study found that drivers' mean response time to an expected stop event was 0.55 seconds. These response times obtained from the physiological signals are far less than the reported brake response time, which is 1.5 seconds (Green, 2000) as generally recommended in the

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Table 4 Summary of the physiological signal data

(1) ACC	Initial acceleration	Max amplitude	Response time	Rise time	Recovery time
N	17	17	17	17	17
Distracted	0.212 (0.087)	−0.314 (0.188)	0.725 (0.134)	0.663 (0.322)	1.741 (0.704)
Regular	0.222 (0.075)	−0.372 (0.162)	0.679 (0.168)	0.894 (0.369)	1.623 (0.639)
***p*-value**	0.339	*0.002*	0.115	*0.021*	0.322
(2) FSR	Max amplitude		Response time	Rise time	Recovery time
N			16	16	16
Distracted	0.297(0.164)		0.621 (0.132)	0.322 (0.141)	1.496 (0.987)
Regular	0.262 (0.189)		0.561 (0.134)	0.487 (0.214)	1.546 (0.869)
***p*-value**	0.542		0.112	*0.006*	0.738
(3) EMG	Max amplitude		Time at max amplitude	Response time	Rise time
N	16		16	16	16
Distracted	0.204 (0.136)		0.510 (0.181)	0.399 (0.135)	0.111 (0.068)
Regular	0.205 (0.123)		0.495 (0.241)	0.310 (0.151)	0.186 (0.122)
***p*-value**	0.944		0.823	*0.057*	*0.027*
(4) EDA	Initial EDA level	Max amplitude	Response time	Rise time	50% Recovery time
N	15	12	12	12	10
Distracted	12.853 (5.133)	15.319 (5.095)	1.815 (0.716)	1.644 (0.736)	1.898 (0.884)
Regular	11.229 (4.989)	14.635 (5.431)	1.513 (0.610)	2.089 (0.736)	1.466 (0.796)
***p*-value**	*0.005*	0.401	0.070	0.067	0.201
(5) PZT	Initial respiration level	Max amplitude	Root mean square of amplitudes	Avg. breath-to-breath interval	Avg. RMSSD
N	17	17	17	17	17
Distracted	1.779 (0.270)	1.936 (0.327)	1.785 (0.272)	2.082 (0.481)	2.242 (0.517)
Regular	1.614 (0.233)	1.810 (0.369)	1.624 (0.240)	2.215 (0.408)	2.396 (0.494)
***p*-value**	*0.011*	*0.085*	*0.013*	0.345	0.323
(6) ECG	Avg. beat-to-beat interval prior event		Avg. beat-to-beat interval post event	Avg. RMSSD prior event	Avg. RMSSD post event
N	15		15	15	15
Distracted	0.748 (0.115)		0.726 (0.121)	0.044 (0.047)	0.145 (0.123)
Regular	0.753 (0.103)		0.760 (0.099)	0.048 (0.061)	0.096 (0.112)
***p*-value**	0.646		*0.041*	0.851	*0.009*

literature. This is not surprising as physiological signals are always the first (among other measures) to react after receiving an external stimulus, and it responds even faster at higher urgencies (Markkula *et al.*, 2016). The rise time reflects the speed at which the physiological signal reaches its maximum amplitude, i.e. the response intensity. The results show that distracted driving needs less time to reach its maximum compared to regular driving. This is interesting because distracted drivers can be described as "delayed but hurry and intensive responders."

5.2.3 Periodic signals – piezoelectric respiration and electrocardiography.
For periodic signals such as PZT and ECG in Table 4 (5) and (6), the time intervals between consecutive two peaks were measured (i.e. breath-to-breath and beat-to-beat), as shown in equation (1). The reciprocal of the average peak-peak intervals, i.e. the frequency, is the breath rate or heart rate, as calculated by equation (2). The breath rate variability or heart rate variability can be indicated using the root mean square of successive differences (RMSSD) of the peak-peak intervals, as can be found in equation (3).

$$PPI_{i,t}^{PZT|ECG} = \mathrm{P}_{r+1,t}^{PZT|ECG} - \mathrm{P}_{r,t}^{PZT|ECG} \tag{1}$$

$$Freq_t^{br|hr} = \frac{60 * N_t}{\sum_{i=1}^{N_t} PPI_i^{PZT|ECG}} \tag{2}$$

$$RMSSD_t^{brv|hrv} = \sqrt{\frac{1}{N_t - 1}\left(\sum_{i=1}^{N_t-1}\left(PPI_{i+1}^{PZT|ECG} - PPI_i^{PZT|ECG}\right)^2\right)} \tag{3}$$

where:
PPI = peak-peak intervals measured from PZT or ECG signal;
Freq = frequency of breath rate (br, unit: breath/min) or heart rate (hr, unit: beat/min) depending on what physiological signal is analyzed;
RMSSD = root mean square of successive differences for breath rate variability (brv, unit: sec) or heart rate variability (hrv, unit: sec) depending on what physiological signal is analyzed;

N_t = number of the total intervals in the predefined study period t;
i = interval index, $i = 1, 2, \ldots, N - 1$;
r = peak index, $r = 1, 2, \ldots, N + 1$; and
t = the predefined study time window.

Some cognitive states may be inferred from respiration amplitude responses after external events (Castegnetti, 2017). In the PZT signal data, the respiration amplitude is significant prior to the event ($p = 0.011$) and is marginal significant post the "stop" event ($p = 0.085$). The heart rate variability indicates mental stress and anxiety corresponding to physiological changes in the autonomic nervous systems. When the emergency stop is required, both heart rate (i.e. RR interval) and heart rate variability (i.e. RMSSD) are significant in distracted driving. Figure 9 shows the prior-post comparison test within one driving situation. Dashed lines with p-values are used to indicate the t-test result. Each bar is marked with the mean in the center and the 95% confidence intervals in the lower and upper boundaries.

Figure 9(a) shows that heart rate has no difference whether drivers are distracted or not ($p = 0.495$) prior to the activation of the stop event. However, the heart rate of distracted drivers increases marginally significantly ($p = 0.096$) than that of regular driving after the stop event. These marginal effects were further demonstrated in Figure 9(b) to be significant in heart rate variability ($p = 0.006$). This is because heart rate variability can identify minor differences, and thus is more informative (Sacha, 2014). Results show that the heart rate variabilities in distracted driving and regular driving increased after the event ($p = 0.006$ and $p = 0.059$). The difference in the increase is significantly different as distracted driving gains more variability ($p = 0.009$).

Both novice drivers (ID = 13, 17) and experienced drivers (ID = 7, 9) have a low level of distraction (i.e. game score), implying that comparatively less attention is assigned to the secondary task. This may be due to these reasons:

- novice drivers are inexperienced in driving and have no extra ability to take the additional nondriving tasks;
- experienced drivers are conservative in safety driving; and
- those experienced drivers are aged 40–60 years, and are relatively unskilled about smartphone games compared to the generation (aged 20–40 years) that grew up with smartphones.

Driver's age and experience were reported to affect the emergency braking (Loeb *et al.*, 2015), especially on the brake response time and intensity. As can be found in Figure 10(a), the results in this study corroborated the findings in previous studies (Loeb *et al.*, 2015). Figure 10(b) shows that the driver's rise time decreases with the increase of either the age or driving experience. The results indicated that a less intense response is conducted by elder drivers as well as experienced drivers.

6. Conclusion and discussions

This paper outlines an explanatory framework for emergency brakes in distracted driving situations, characterized by driver demographics, vehicle kinematics and more importantly, physiological signals. This study extends the literature findings on the psychophysiological measures of distracted driving when an emergency stop is required. In automated driving mode, drivers do not need to monitor the environment all the time and can engage in their secondary tasks. When the autonomous system detects an emergency situation that requires the driver to take over, the brake features in this study work as a preliminary study. As take-over quality deteriorated for distracted drivers (Zeeb *et al.*, 2016), this study underlined how quick drivers could respond to the "take over" notice (released by the autonomous driving system) and resume vehicle control. Eventually, the proposed framework may serve to guide the next step of this study on the potential causal role of distraction load when drivers are in autonomous vehicles.

Recently, various forms of wearable physiological monitoring devices are commercially available. Therefore, it is possible to get the physiological signals of drivers to improve the ADAS. The driver assistance system would moderate the response time when distracted (Zeeb *et al.*, 2016), and it would provide a reference for monitoring the physiological state (Hamdani and Fernando, 2015; Vetter *et al.*, 2017). The driver state could provide information to a system that decides the way to adapt the vehicle based on the demands of the task relative to the distraction state (NHTSA, the National Highway Traffic Safety Administration, 2004). The particularity of this

Figure 9 Heart rate comparison (a) and heart rate variability comparison (b) between distracted driving (i.e. dis) and regular driving (i.e. reg) prior to and post to the event, respectively

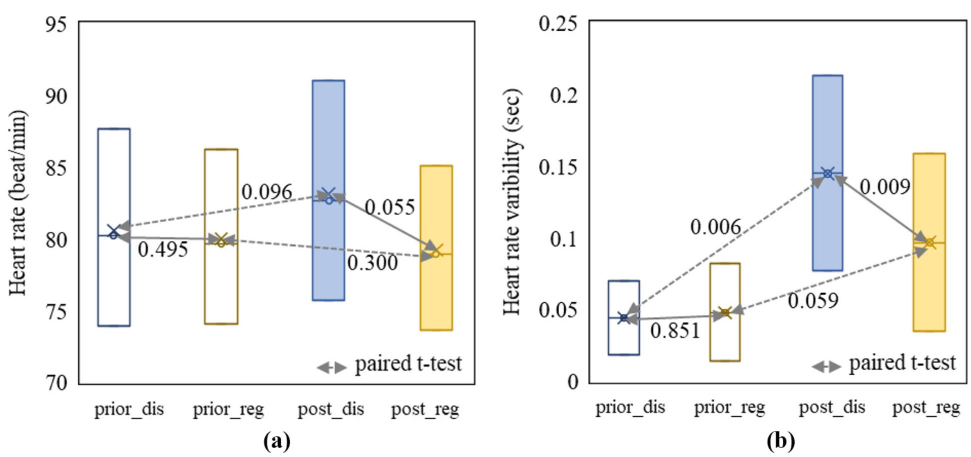
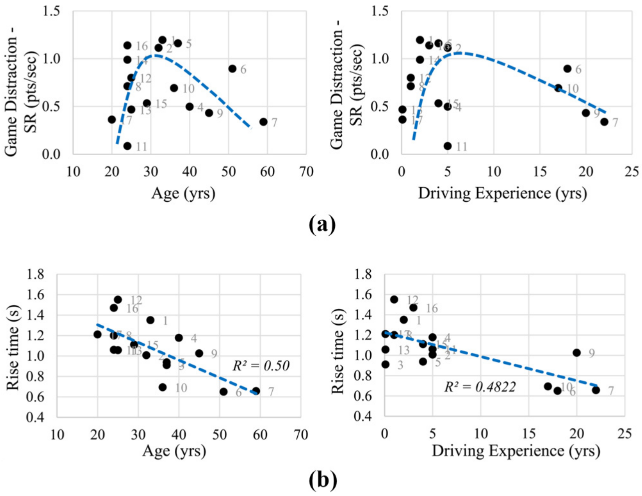


Figure 10 Driver's age and experience (Driver IDs are labeled next to the data points)



Notes: (a) Level of distraction versus drivers' age (left) and driving experience (right); (b) rise time from FSR signal versus driver's age (left) and driving experience (right)

experiment is the simplification of the driver's response to the emergency stop event. In most of the previous distraction experiments, the driver first perceives an event, decides and produces a response, i.e. the classical perceive–decide–response mode. In this study, the driver was informed of the emergency brake and performed it immediately after a quick external condition check. In this study, however, the experiment assistant acted as the perceiver and the decision-maker of the event. The driver's physiological states can be monitored so to leverage technology to improve road safety, such as to assist in driver distraction detection and warning system for crash avoidance. This study demonstrates that the drivers are physiologically reactive to urgent stimuli, especially drivers under distraction. It provides a viable means of detecting and distinguishing distracted driving status. The main findings are summarized as below.

Before the emergency stop event, distracted drivers run with a relatively low speed (SPD, $p = 0.002$) and are generally more nervous (EDA, $p = 0.005$; PZT, $p = 0.011$). When responding to the stop request, distracted drivers are delayed in perception (EMG, $p = 0.057$; EDA, $p = 0.070$), and hurriedly reached to the maximum intensity response indicated by the maximum amplitude (PZT, $p = 0.085$; ECG, $p = 0.041$) and the rise time (ACC, 0.021; FSR, $p = 0.006$; EMG, $p = 0.027$; EDA, $p = 0.067$) and do not get the full brake (SPD, $p = 0.004$; ACC, $p = 0.002$). These lead to an escalated stress and anxiety (PZT, $p = 0.013$; ECG, $p = 0.009$). All these results help to characterize and differentiate the distracted drivers.

When the response time collection method moves from vehicle kinematics (i.e. SPD, FSR, ACC) to physiological signal (i.e. EMG, EDA), more clear evidence can be found to distinguish a distracted driving state. The order of the response time: EMG < FSR < ACC < SPD makes good sense as the driver firstly lifted his or her right leg (EMG), pressed the brake pedal (FSR), the vehicle decelerated (ACC) and then captured by the trajectory device (SPD). The distracted drivers are physiologically more reactive to the emergency stop stimuli, exhibiting significant increases in the intensity and time of the response. Among all the physiological parameters tested in this study, response time and rise time are sensitive and recommended in distracted driving studies. Although amplitude is fundamental in reflecting the reaction intensity, it should be cautious as it may require a more accurate data acquisition system with multiple channels for each signal.

One of the limitations of the study is the small sample size. The results, therefore, should be interpreted with caution and wait for repetition to arrive at a firm conclusion. A repeated measure of multilevel modeling that adopts the driver-nested data structure is suggested in the future study when the data sample is enlarged to capture the within-subject variability. The design of the experiment could be further improved as well. For example, the order of the two driving tasks carried out by the participants may be reversed to help eliminate biases caused by the previous driving experience. What's more, the accuracy of the measurements was dependent on the reliability of the assistant's action time. Although the body sensor system was sensitive to many signals in a preexperimental test (e.g. deep breathing, muscle contracting and sudden frightening), its accuracy has not been validated, especially given driving is a complicated process that many factors may be out of control.

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Corresponding author

Li Zhao can be contacted at: lizhao@unl.edu