Methodology and Mobile Application for Driver Behavior Analysis and Accident Prevention

Alexey Kashevnik, Igor Lashkov, and Andrei Gurtov

***Abstract*—This paper presents a methodology and mobile application for driver monitoring, analysis, and recommendations based on detected unsafe driving behavior for accident prevention using a personal smartphone. For the driver behavior monitoring, the smartphone's cameras and built-in sensors (accelerometer, gyroscope, GPS, and microphone) are used. A developed methodology includes dangerous state classification, dangerous state detection, and a reference model. The methodology supports the following driver's online dangerous states: distraction and drowsiness as well as an offline dangerous state related to a high pulse rate. We implemented the system for Android smartphones and evaluated it with ten volunteers.**

***Index Terms*—Driver behavior, smartphone, computer application, context awareness, intelligent system, mobile application.**

I. Introduction

According to the statistics of traffic fatalities for the first half of 2016, a total of 17,775 people died in motor vehicle traffic crashes in the U.S. [1]. This represents an increase of about 7.7 percent compared to the 32,675 fatalities that were reported in 2014. The U.S. Department of Transportation's most recent estimate of the annual economic cost of crashes was $242 billion dollars. Major contributors to the death toll are alcohol, speeding, lack of safety belt use, and other problematic driver behaviors. Death rates vary by vehicle type, driver age, gender and other factors. Therefore, driver behavior analysis is an important and trending research topic at the moment [2].

Advanced Driver Assistance Systems (ADAS) are aimed to simplify and aid the driver in monitoring, warning, braking, and steering tasks through a variety of assisting technologies. Primary goal of these systems is to provide safety for a driver and help to prevent road accidents. ADAS systems are undeniably one of the fastest growing areas in the automotive industry. When designed with a safe human-machine interface, they offer increased car and road safety by offering technologies that alert the driver to potential problems, helping to avoid collisions and accidents. Adaptive features provide options for adaptive cruise control, automatic braking, GPS / traffic warnings integration, alerting for other dangerous drivers while indicating correct lane position and blind spots. However, Business Growth Insights (BCG) research indicated that one reason consumers are slow to adopt ADAS features is the cost of such systems. These systems are usually accessible only on the luxury segment of cars as additional features and require additional hardware to be installed in the vehicles.

In this paper, we present a methodology and a mobile application for dangerous states detection and recommendations generations for the driver using built-in front-facing camera and sensors of the driver's personal smartphone. The precision of such application is certainly less than of ADAS system since ADAS uses the specialized equipment designed for specific purposes in contrast with smartphones. However, our evaluation on real drivers shows that the developed application successfully determines dangerous states and aids to provide recommendations for a driver. Together with the team from National Institute of Advanced Industrial Science and Technology (Japan), authors evaluate the development application for two-wheeled self-balancing vehicles (Segways) [3]. Together with colleagues from Trinity College Dublin [4], authors propose an approach to e-bike rider intelligent support based on the methodology proposed in the paper.

This paper expands on our prior work [5]–[9] that are concentrated on particular parts related to the driver behavior analysis and recommendations, but in contrast, this paper combines and enhances the research. The paper has the following merits:

- classification of the dangerous states that can be determined based on information from smartphone front-facing camera and sensors;
- methodology for driver behavior analysis for dangerous states determination based on information from smartphone front-facing camera and sensors;
- dangerous states identification and camera processing scheme that are aimed to define dangerous state determination scheme and identify frames from front-facing camera that are need to be recognized;
- high pulse rate determination approach description;
- evaluation of the system, describing the statistical analysis of the system use by a group of drivers and determination of drowsiness, distraction, and high pulse rate.

The rest of the paper is organized as follows. Section II presents the related work. Section III describes our methodology that includes the proposed dangerous state classification, dangerous state detection, and the reference model

Manuscript received January 20, 2017; revised August 3, 2017, November 30, 2017, May 15, 2018, October 12, 2018, February 27, 2019, and April 24, 2019; accepted May 17, 2019. This work was supported by the Russian Science Foundation under Grant 18-71-10065. The Associate Editor for this paper was M. Menendez. *(Corresponding author: Alexey Kashevnik.)*

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Digital Object Identifier 10.1109/TITS.2019.2918328

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

TABLE I
COMPARISON OF ADAS MOBILE APPLICATIONS FOR DANGEROUS STATE DETECTION BY DRIVER SAFETY FUNCTIONS

Technology / Application	iOS	Android	Aggressive driving	Adaptation to a driver	External sensors	Statistics accumulation	DD	ID	Driving style	Context
CarSafe	–	–	+	–	–	–	+	+	–	+
Driver behavior profiling [23]	–	+	+	+	–	+	–	–	+	+
Mobile healthcare [24]	–	+	–	–	+	–	+	–	–	–
Sensoric [28]	–	+	+	–	+	–	+	+	+	+
DriveSafe	+	–	+	–	–	–	+	+	+	+
Anti drowsiness alarm	+	–	–	–	–	–	+	–	–	–
Facial fatigue and driver AI Drowsiness detection	–	+	–	–	–	–	+	–	–	–
Fujitsu driver drowsiness	–	+	–	–	+	–	+	–	–	–
SenseFleet [29]	–	–	–	+	–	+	–	–	+	+
DMS [18]	–	+	–	–	–	+	+	+	–	+

TABLE II
COMPARISON OF ADAS MOBILE APPLICATIONS FOR DANGEROUS STATE DETECTION BY USING SMARTPHONE FEATURES

Feature / Application	Front camera	Rear camera	GPS	Accelerometer	Gyroscope	Microphone	Pulse sensor
CarSafe	+	+	+	+	+	+	–
Driver behavior profiling [23]	–	–	+	+	+	–	–
Mobile healthcare [24]	–	–	–	–	–	–	–
Sensoric [28]	–	–	+	+	+	–	+
DriveSafe	+	–	+	–	+	–	–
Anti drowsiness alarm	+	–	–	–	–	–	–
Facial fatigue and driver AI drowsiness detection	+	–	–	–	–	–	–
Fujitsu driver drowsiness	–	–	+	–	–	–	+
SenseFleet [29]	–	–	+	+	+	–	–
DMS [18]	+	–	+	+	+	–	–

of the proposed system. The implementation is presented in Section IV. Main results are summarized in Conclusion (Section V).

II. RELATED WORK

There are plenty of driver behavior monitoring and analysis solutions providing safety systems working on the basis of cameras, radar or Light Identification Detection and Ranging (LIDAR) technologies [10]–[13]. Some safety features are already built into modern vehicles by producers or are available as an add-on package. However, aftermarket solutions gain popularity and are also becoming available for late model cars. Integrated systems usually have expensive price or limited to a specific or concrete car model that highlight the motivation of the smartphone-based application development in this area.

A more affordable option to apply driver safety features is to use video cameras installed inside the cabin of the vehicle. Dashboard cameras, single separate video surveillance devices monitor the road or the driver [14]. Due to its design, it is easy for a driver to mount a video camera on the windshield of the vehicle, or remove it without any difficulties or cost. Due to massive use of dashboard cameras inside the vehicle cabin, the study [15] demonstrates technique to automatically detect driving corner cases from camera videos and inertial sensors of sudden human driver reactions and rare visual events through a trained autoencoder deep neural network.

Mobile applications providing advanced safety features are presented in Table I and Table II. In these tables “+” means that the considered application supports technology / feature and means that it does not have one. CarSafe [16] is a driver safety application for Android phones that detects and alerts drivers to dangerous driving conditions and behavior. Another study [17] allows to detect and classify specific types of risky driver behavior using the smartphone sensors. Risky driver behavior is divided to following groups: weaving, swerving, side-slipping, fast U-turn, turning with a wide radius and sudden braking. Each of these types presents a unique set of patterns on orientation and acceleration. Many studies relate to classification of driving patterns, describing the sequence, success rate and time parameters of driver activities for certain situations [18]–[20]. These works extract and classify driving event types and estimating the output driving style [21], [22] for different purposes: evaluate risk driving behavior to pay attention or improve driving skills, estimate fuel consumption efficiency; provide driving statistics report for third party organizations (for example, Android application AXA Drivesafe.[1]) The results of the study [23] show that gyroscope and accelerometer sensors built into smartphone are most suitable to detect driving events; machine learning algorithms including multilayer perceptron and random forest perform best in their experiments. Based on naturalistic and driving simulator experiments, another research study [18] involves processing of smartphone’s sensor data gathered from a driver monitoring system (DMS) to analyze driver’s drowsiness and distraction.

Other approaches for automatic detecting dangerous situations monitors in-cabin driving behavior in real-time and determine drowsiness state [24]–[26], and DriveSafe [27].

[1] https://play.google.com/store/apps/details?id=com.mydrive.axa.drivesave

Their smartphone-based systems consisting of a mobile application and a sensor module relies on the analysis of electroencephalogram and respiration signals of a driver to measure its fatigue state while driving. To address the problem of detecting situations whether the drivers are involved in risky driving, the study [28] analyses the influence of the driver's environment and activities on the driving style at the beginning of the trip. Additionally, authors estimate the strength of the car door opening and closing based on the data from the accelerometer sensor. Anti Drowsiness Alarm[2] is an Android mobile application able to continuously monitor the driver's eyes state and recognize drowsiness using the front-facing camera. Quite similar technique for drowsiness recognition can be found in other application named Facial Fatigue and Driver Drowsiness Detection AI.[3] It uses image recognition algorithms to recognize facial features of the driver and alert him or her with beep sounds.

The use of external sensors can aid to increase accuracy of smartphone sensors and provide additional information about driver behavior. This way the mobile application Fujitsu Driver Drowsiness[4] proposes an approach based on the use of the wearable sensor device that analyses driver biorhythms to detect their drowsiness state. It continuously monitors driver's pulse through the sensor attached to the earlobe, measures any sign of the drowsiness and notifies driver. Also, the calibration algorithms are used to adapt this sensor device for a driver and, therefore, improve overall detection accuracy. This Android-based mobile application gives the driver an opportunity to look through the generated trip report and analyze potential routes causing drowsiness state.

SenseFleet [29] presents a mobile sensor-based vehicle independent platform for a driver that identifies driving maneuvers, recognizes risky driving events and scores each individual driver using context-relevant information, including route topology, weather conditions and time of the day. Acceleration, braking, steering and over-speeding events are detected on the basis of the motion sensors and GPS data. To detect every risky driving event, including sudden or aggressive maneuvers, the platform uses a set of fuzzy logic rules. Finally, this mobile sensor platform distinguishes calm and aggressive drivers.

The main difference of the proposed approach from the existing ones is the adaptation of the behavior analysis system to the driver. This adaptation is based on the driving statistics that is kept while the system utilization.

III. Methodology for Driver Behavior Analysis and Accident Prevention

Our methodology utilizes an ontology for modeling a driver in a vehicle and acquiring information and knowledge about them for the driver behavior analysis. The ontology provides possibilities to structure the knowledge about the driver and vehicle and use this information for dangerous states identification and recommendation generation [7]. Information and knowledge are acquired with driver's smartphone using the front-facing camera, accelerometer, gyroscope, Global Positioning System (GPS), microphone and navigation maps for the driver information flow (driver context). The main goal of driver behavior analysis is unsafe driving behavior recognition and recommendations for decreasing the risk of accidents. The section describes the dangerous state classification, dangerous state detection, and reference model of the proposed system for driver behavior analysis and accident prevention.

A. Dangerous States Classification

Related research analysis allows to determine the following dangerous states for the driver that can be determined based on information from smartphone sensors: drowsiness, distraction, high pulse rate, drunk driving, aggressive driving, and stress. We use the following information from smartphone sensors for that purposes (see Fig. 1). Face images from front-facing camera are captured and analyzed to determine such calculated parameters as eyes openness, head yaw angle, head pitch angle, and mouth openness. We track these parameters and analyze them during the time t_s (time of dangerous state recognition) for determination of the driver visual cues (PERCLOS, head movements, yawning). PERCLOS is the percentage of eye closure that is the main visual cues signaling the drowsiness dangerous state. Yawning is the visual cues that also signals to the driver drowsiness. Analysis of the head movements allows to recognize the distraction dangerous state. The analysis of the PERCLOS and yawning indicators allows to recognize the drowsiness dangerous state.

We propose to classify determined dangerous states into two main sets: detected online and offline. Online detected dangerous states are dangerous states that have to be determined in a small period of time t_s (we identify it as two seconds by default and are going to develop an algorithm to determine it personally for the driver based on driving history). Two seconds are corresponded to the distance to the vehicle ahead of about thirty meters (recommended by traffic rules). The standard speed limit common in urban areas in Russia is sixty km per hour then for this speed thirty meters correspond to two seconds. Offline detected dangerous states are dangerous states that have to be detected in a certain period of time more than t_s. However, the detection time should be reasonable because if the dangerous state is detected by few hours sometimes the trip can be completed, and such detection is not needed for the driver. In this case when we talk about offline detected dangerous states on the minutes scale. In this case, calculations of the offline detected dangerous states can be implemented in a cloud if needed.

Another information from smartphone sensors is the forehead color that is used to calculate high pulse rate in an offline detected dangerous state. The preliminary experiments conducted with pulse rate determination show that it is not possible to calculate the exact value of pulse rate but it is possible to say about high pulse rate (more than 110-120 bpm) and normal pulse rate (about 60-80 bpm) that can be caused by drunk driving, aggressive driving and / or stress condition. Gyroscope and magnetometer sensors are used to determine

[2]https://play.google.com/store/apps/details?id=de.antidrowsinessalarm

[3]https://play.google.com/store/apps/details?id=com.raboijaking.eyefatigue detector

[4]https://play.google.com/store/apps/details?id=com.fujitsu.vehicleict.drive rdrowsinessdetector

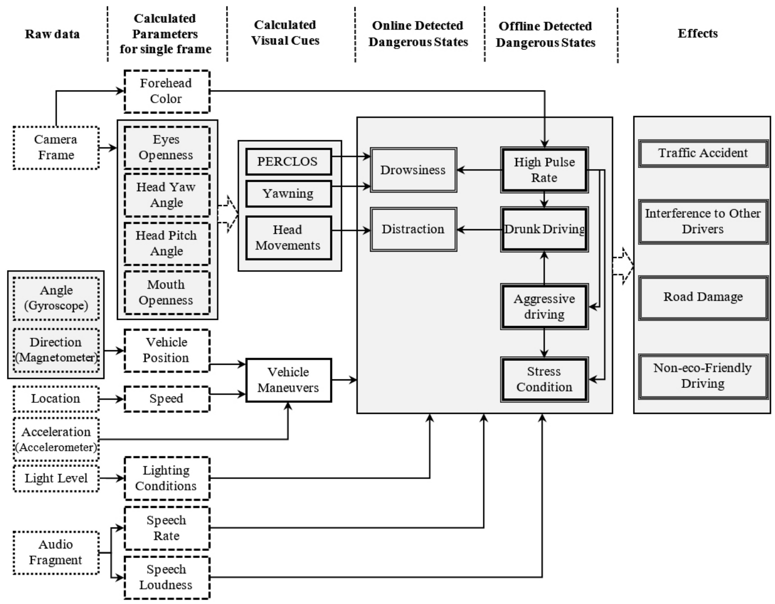

Fig. 1. General scheme of smartphone data utilization for dangerous states identification.

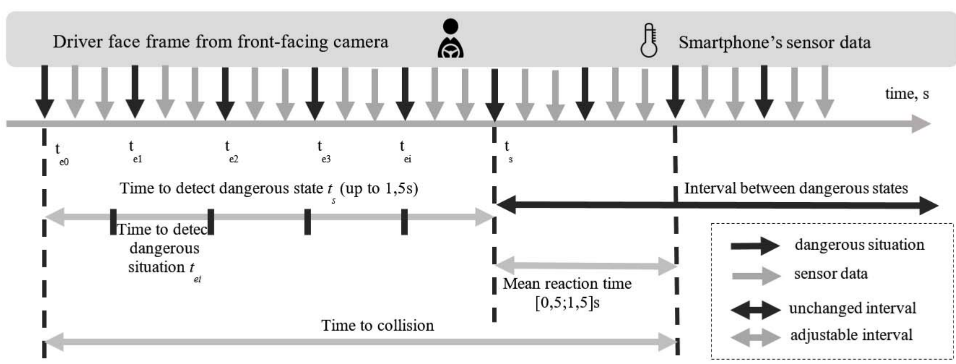

Fig. 2. Online detected dangerous states identification scheme.

calculated parameter of vehicle position that together with the speed parameter (calculated from smartphone location information) and acceleration are used to calculate vehicle maneuvers. Vehicle maneuvers are important for all dangerous state detection. For example, if the vehicle speed is zero it is not necessary to monitor the driver face since he/she is not driving and does not need to concentrate on the road. Another example is the distraction determination. If the driver looks to the left and after that the vehicle turns to the left it should be recognized as normal state but not distraction one. Lighting sensor is used to determine lighting conditions in the vehicle cabin. Lighting conditions have to be considered during the dangerous state identification. For example, if there is not enough light in the cabin, the trust level to the front-facing camera recognition should be less than in situation with the high lightness level. The last considered smartphone sensor is the microphone that is used to determine the noise level in the vehicle cabin as well as speech rate and speech loudness. For example, if the driver speaks with a passenger, the lighting condition is low, and a drowsiness dangerous state is determined we should skip this dangerous state since the driver cannot sleep while talking.

Aggressive driving, stress dangerous states, and drunk driving are determined based on calculated pulse rate and vehicle maneuvers. The following effects have been identified that can be caused by the driver dangerous states: traffic accident, inference to other drivers, road damage, and non-eco-friendly driving. Traffic accident and interference to other drivers can be caused by all dangerous states. Road damage and non-eco-friendly driving are related to the aggressive driving dangerous state when a driver accelerates a vehicle quickly.

B. Dangerous States Detection

As mentioned in Section III-A, we classify dangerous states to online detected and offline detected. Online detected dangerous states identification scheme is presented in Fig. 2. Time to detect dangerous state t_s can be presented in a form of time series that the parameters of driver behavior are continuously collected based on the information from front-facing camera and sensors of the smartphone. Dangerous driving state is determined based on the analysis of the dangerous situations t_{ei}. One of the key parameters is an overall number of dangerous situations in time interval, denoting one or another dangerous state t_s. This parameter depends on the time of processing dangerous situations t_e and the driver's reaction time $treaction$. According to the studies in the field of exploring reaction time and time to collision parameters and self-conducted experiments on image processing with smartphone front-facing camera, the following formula was proposed to detect the number of dangerous situations that have to be processed to detect the dangerous state:

$$n = 1 + (\frac{E}{(t_{reaction} + 0,5)} * 2)^2,$$

where $n \in [1, 101]$ is a dimensionless quantity, equal to the number of measured dangerous situations, $E \in [1, 5]$ is a factor of smartphone computing power, $t_{reaction} \in [0.5, 1.5]$ is a driver's reaction time. Hence, with increase (decrease) of processing time for one dangerous situation or decrease (increase) driver reaction time the parameter n increases (decreases), thereby enabling high accuracy of dangerous state detection in driver behavior, processing the greater number of potential dangerous situations in given time. Vice versa, when n decreases that leads to increase of probability of missing or false detection of one or another dangerous state, that affects the further work of the driver's recommendation generation module.

Assuming the detection of dangerous situations should work without processing of each incoming frame, this process can quickly drain the smartphone battery. We propose to consider the following scheme for skipping camera frames. The generalized process of processing camera frames is shown in Fig. 3. Time to collision parameter (t_s) used for detecting dangerous situation $t_{e(i)}$ in each frame taken from the front-facing camera.

A number of frames exceeding the high limit of maximum processed frames n_{limit} can be evenly skipped while recognizing dangerous situation without strong influence on the accuracy of the ongoing process. This is achieved by dividing the time of dangerous state recognition into time periods for recognizing unsafe driving behavior and skip-time intervals. Skip-time interval is a period of time during which driver behavior recognition task can be skipped for the frame received from the camera. This parameter is estimated as the ratio of time needed for dangerous state recognition t_s and maximum count of processed frames n_{limit} for the dangerous state, excluding the average processing time of a single frame t_e^{avg}.

Recognition of the offline dangerous states depends on the context situation. As we mentioned before it can be implemented in a smartphone as well as in a cloud since there is enough time for information transfer. In this case, if the driver has a low-grade smartphone the recognition is implemented in a cloud. If the driver has a high-grade smartphone the recognition is implemented in the smartphone.

We implement the analysis of the high pulse rate in the following way. We track the face of the driver, then we determine the area of interests (forehead), after that we calculate mean color, and then transform to the frequency that characterizes the pulse rate. The determination algorithm relies on color change in a region of user's face. The region of interests for

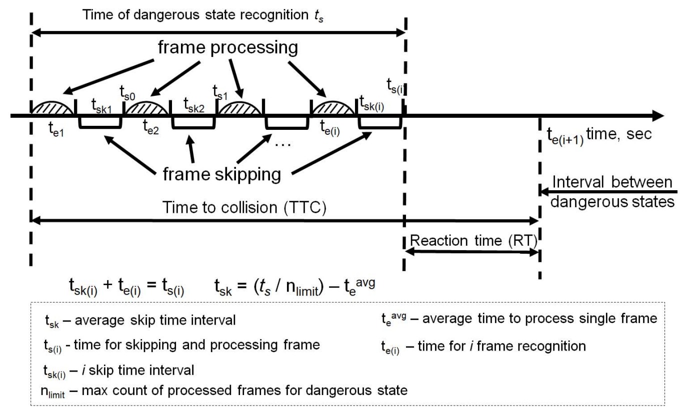

Fig. 3. Camera frames processing.

forehead is a set of pixels that have its values for red, green, and blue component in form of an integer value from range [0, 255]. For each component the algorithm calculates its mean value by averaging the component's value for all pixels in the region of interests. The result is three mean values for red, green, and blue components. The mean value of those three numbers is the data extracted from the frame and it is added to the data buffer.

We propose to track images of the driver face from front-facing camera using OpenCV and DLib to extract visual characteristics of the driver, obtained from the frames in the video sequence, that typically characterize his/her numerical degree of drowsiness and distraction. The flow chart for dangerous states recognition is presented in Fig. 4. Visual cues relevant to the drowsiness state are percentage of closure of eyelid (PERCLOS), eye-blink time, eye-blinking rate, eye gaze, pupil movement and eyelid movement. Existing research findings have shown that PERCLOS parameter is an effective indicator for evaluating a driver's drowsiness. PERCLOS formally represents the proportion of time within one minute that eyes are at least 80% closed [30]. The PERCLOS parameter is continuously computed and the driver is considered "drowsy" if PERCLOS exceeds a threshold of ($P_{MAX} = 28\%$) [31]. Another parameter is the speed of blinking, giving a permissible range of $B_{TIME} = 0.5 - 0.8$ seconds per blink [31]. One more indicator of drowsiness is yawning. If the driver makes more than $Y_{MAX} = 4$ yawns in $Y_{TIME} = 1$ minute, we consider the driver is in the dangerous state [31]. And finally, the fourth indicator of this dangerous state is the head nodding. If the number of head nodding exceeds $N_{NUMBER} = 4$ in $N_{TIME} = 2$ minutes, the drowsiness is inferred [31]. In case of distraction monitoring, if the driver's head is not facing forward (angle $R_{MAX} \geq 15°$ rotation relative to facing directly forward) for longer than $HR_{MAX} = 2$ seconds while the vehicle is moving forward (while a positive speed is reported by the accelerometer) and not turning as reported by the turn detector (which is based on the gyroscope readings) then a dangerous driving event is inferred.

C. Reference Model

Fig. 5 presents the reference model of our system for driver behavior analysis and accident prevention. It consists of four

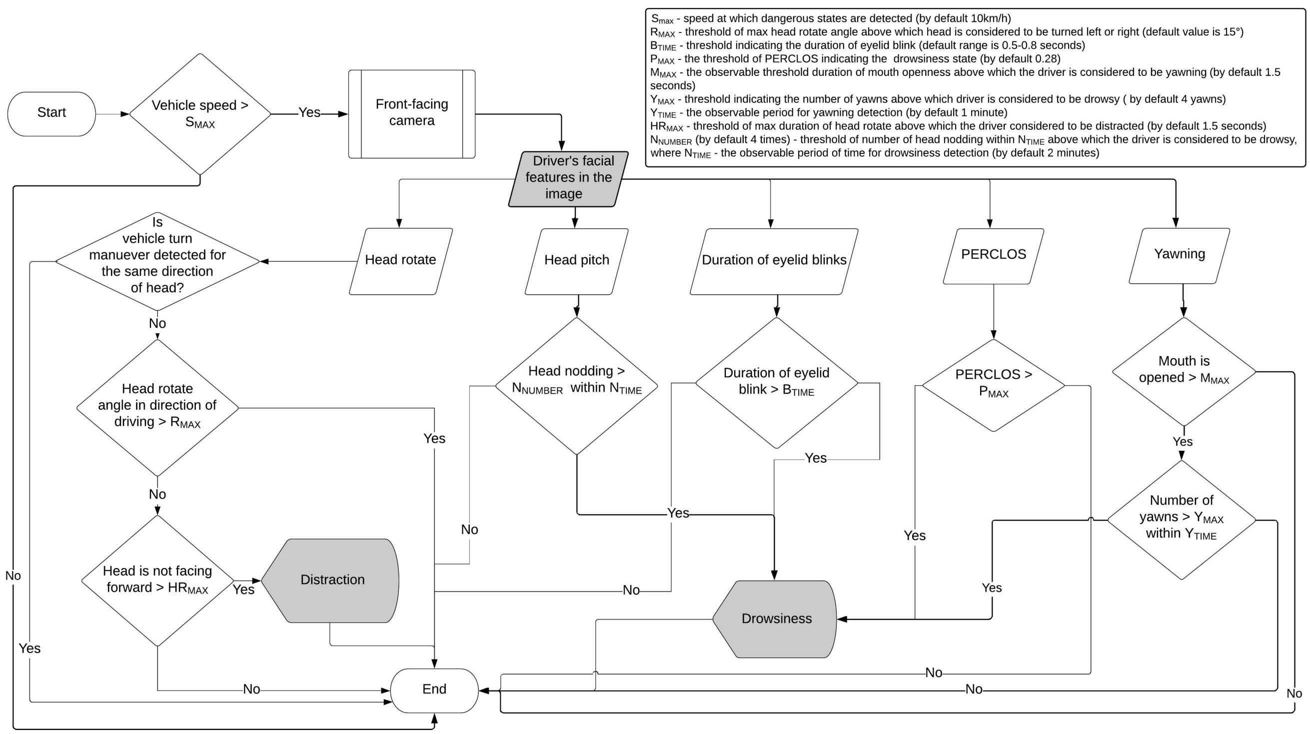

Fig. 4. Flow chart of dangerous states recognition for in-cabin pipeline.

main modules: of a driver, a vehicle, a smartphone, and a cloud service. The smartphone module tracks the driver face, vehicle (e.g., speed, acceleration), and in-cabin characteristics (e.g., noise level, lightness), presents the driver recommendations, and sends the information to the cloud service. The front-facing camera and sensors of the smartphone (GPS, accelerometer, gyroscope, magnetometer, microphone) collect the data. Front-facing camera observes driver's visual cues from a sequence of video frames. Information from smartphone sensors is collected for estimating various quantities such as the vehicle's speed, acceleration, braking, and the current location of the driver that constitutes the context. Dangerous situations are determined based on the context. Recommendations are generated based on the determined dangerous situations and context and are aimed to prevent road traffic accident at the time. To attract the driver's attention, the in-cabin audio system is used. The determined dangerous situation and context is stored for further analysis and transferred to the cloud service. If the Internet connection is not available, the system works in offline mode and accumulates the statistics in the smartphone. When the internet connection becomes available, the system uploads the accumulated statistics to the cloud service.

The cloud service is responsible for storing driving statistics, driver's preferences, specific features while driving, grouping drivers, determining behavior patterns. It also estimates driving preferences and style as well as determines driver preferences to utilize this information for further recommendations generation. Also, the cloud service determines the system reaction time, generates reports for consumers (for private drivers, administrators in car parks, and insurance companies representatives), and manages the access control to the private information. To implement this functionally we propose to keep the statistics acquired by the smartphone in the cloud. The statistics includes all information acquired from smartphone camera and sensors as soon as calculated characteristics (such as head rotation angle and PERCLOS). The cloud service also stores such service information as smartphone characteristics, application usage statistics.

The driver is described by a certain number of visual cues and mental states including head position, its movements, PERCLOS, eye-blink frequency, eye gaze [32], [33] and yawning obtained from front-facing camera. Smartphone microphone determines if the driver is speaking or not at the moment. All these parameters are involved in dangerous states recognition relevant to the context helping to avoid distraction and drowsiness dangerous states while driving by generating recommendations for the driver.

In order to improve the quality of locally collected data processing, various sources of open data can be used. Currently, most business and governmental entities compile statistics reports. The frequency of accommodation is usually from one month to one year depending on the dynamic of problem area. In addition, the increased use of the Internet of Things allows to automatically collect and publish similar statistics for later use. As examples applicable to the task of the project the following sources of open data can be mentioned: road services (state of the roads, current maintenance, changes in traffic patterns and parking lots), police (road accident statistics classified by type, road rules violation statistics), municipality (public transport routes, paid and free parking, load level of the city street network). Each of the above

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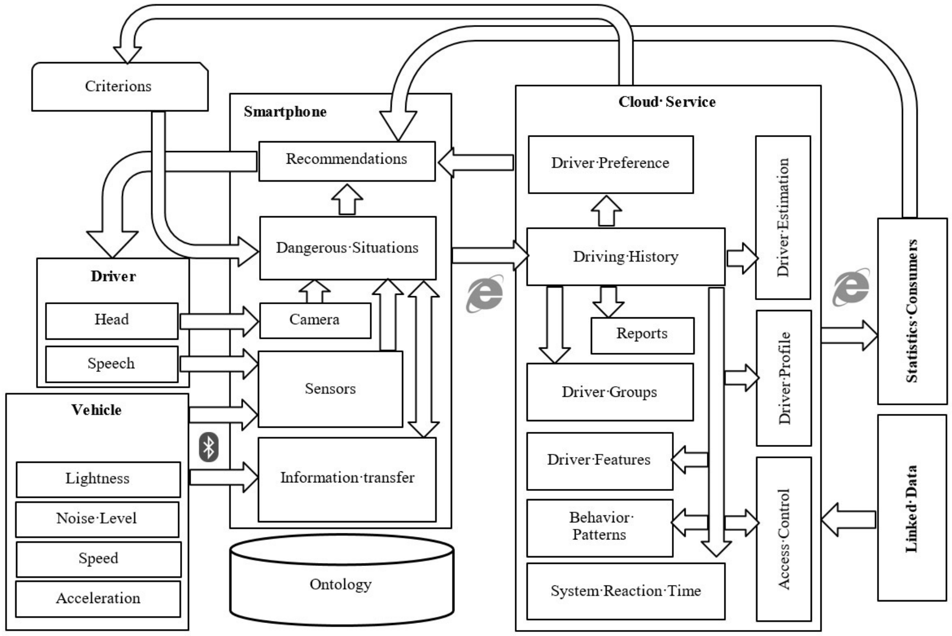

Fig. 5. Reference model of the proposed driver behavior analysis and accident prevention system.

examples can be used both to develop recommendations for the driver of the vehicle, and to form generalized statistics for third-party services, such as transport companies, insurers' services. When establishing links between information elements, we can talk about Open Linked Data. In this format, information can be used by semantic applications to form solutions and new knowledge relevant to the current situation.

D. Recommendation Module

An individual driver behavioral strategy is proposed for each dangerous state to avoid. The driver's ability to perceive alerts can be presented as follows: warning beep or/and voice of the alert; a vibration of the smartphone device; flashing the smartphone screen; an alerting icon or/and a textual message on the smartphone or/and vehicle screen. As immediate steps to prevent dangerous road situations while driving, drivers can follow such recommendations, as pull over and take a nap; drink two cups of coffee or other equivalently caffeinated beverages at the nearest cafe or gas station; listen to radio or music; talk to passengers; cool the car interior; sing yourself or have a rest at the nearest hotel. Short naps of 15–20 minutes can improve well-being, performance and short-term alertness [34]. Longer naps may result in sleep inertia, leaving the driver groggy and disoriented, which can be detrimental to driving. Coffee or another type of caffeine beverage can promote the short-term alertness and prevent the possible driver's drowsiness state. The smartphone's sensor data, that comprises the driver's current actual location, retrieved by the GPS sensor, can be utilized to search and check whether there are any available cafes, hotels or gas stations close to a driver. On the one hand, if the driver is on the motorway and the remaining travel time exceeds the distance of 100 km, the nearby rest places within the distance of 50 km will be provided for a driver. On the other hand, in case the driver is in the urban area, the search radius of possible places of rest will be limited to 20 minutes of driving. If the worst case occurs and no places of rest, including cafes, hotels and gas stations, considering the driver's current location, had been found, the driver will be given a number of recommendations to prevent the occurrence of dangerous state, straightway. In this situation, possible recommendations to avoid driver's drowsiness can be spoken as turn on radio and music, start talking with passengers, cool the car interior, sing yourself or pull over and take a nap.

IV. Implementation

To implement the presented methodology authors develop the mobile application (for Android-based smartphones) and cloud service. Current implementation of mobile application contains about 109 000 lines of code. The following steps realized the driver behavior analysis and accident prevention system.

- First of all, we implemented the flowchart presented in Fig. 4 to determine a dangerous situation at the moment. To determine head parameters we have used the OpenCV and Dlib computer vision libraries;
- After that, we implemented dangerous state determination based on Fig. 2 and Fig. 3. Fig. 2 shows how to detect a dangerous state based on a number of detected dangerous situations. Fig. 3 shows an approach to determine the moment when the driver's face should be tracked in the best way.
- Then, we developed a module for tracking accessible smartphone sensors and its analysis to determine if the determined dangerous state relevant to the context situation (e.g., if the driver stays in a traffic jam, the distraction dangerous state is not applicable).

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TABLE III
DANGEROUS STATE DETERMINATION STATISTIC EXAMPLE

Date/Time	Lat/Long	Speed	Acceleration	Rotation position	Shakiness	Lightness	Head angle (pitch / yaw)	PERCLOS	Processing time	Frames processed
12/02/2019 05:16:45	59.949, 30.246	20	13.82	-34.4, 8.24 -86.5	1.15	0	-22.76, -3.88	0	1225	7
12/02/2019 05:23:17	59.953, 30.267	68	11.77	-88.39, 0.30, -89.53	1.16	1	-4.10, -3.88	1	1608	9

Fig. 6. An example: a smartphone mounted on a vehicle's windshield. The mobile application recognizes a dangerous state.

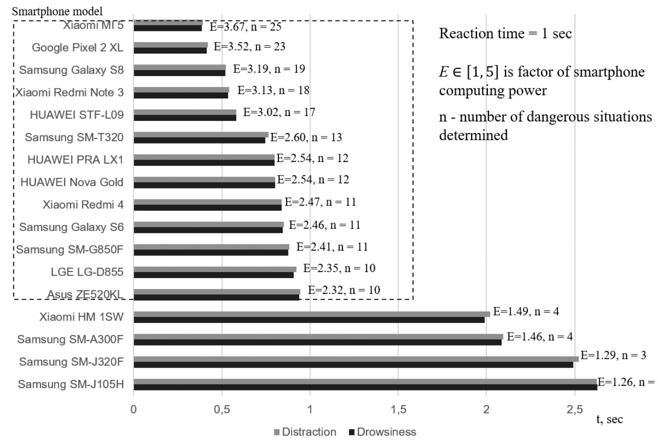

Fig. 7. Dangerous situation detection time (sec.) for different devices participated in the experiments.

- After that we developed the recommendation module described in Section III-D.
- Then, we developed the cloud service that accumulates statistics of the mobile application that includes the determined dangerous states, generated recommendations, and context of the driver and the vehicle calculated based on accessible smartphone sensors.
- At the end, we are linking together the mobile application and the cloud service to accumulate the statistics.

Fig. 6 illustrates a smartphone mounted in a vehicle windshield. Smartphone front-facing camera is directed to the driver's face that allows to recognize dangerous states. The user interface overlays alert icons to the camera screen that correspond to dangerous driving events. When a face is detected, it is marked by a rectangle around the head in the camera image. The face detector marks landmarks by circles. The mobile application is launched in overlay mode that provides possibilities to the driver use the favorite navigation application.

The example of statistics of distraction and drowsiness events recognition specific to the concrete driver is shown in Table III. It lists determined dangerous states as well as context information including the date and location of commute, city or country driving, vehicle speed and acceleration and lightning conditions. The table includes a head turn angle indicator that explains distracted state of driver as soon as parameters describing the drowsiness of the driver: PERCLOS and the probability of openness of the eyes.

For evaluation of proposed system, real-life experiments have been carried out with ten volunteer drivers of different ages in real moving vehicles in the city and in the countryside at different times of the day. During the experiments the system determines 88 drowsiness and 231 distraction dangerous states. For the feedback accumulation the speech recognition interface (based on Google services) has been plugged-in. It can recognize "yes" or "no" phrases from the driver. After every recognized dangerous state, the application asks drivers if he/she really turned the head, closes the eye, or yawn. The drivers provided feedback (see table IV) that the dangerous states have been determined mostly correctly. The accuracy measure of image processing algorithms directly depends on certain circumstances including diversity of people (facial expressions, reflections on glasses), varying lightning conditions (insufficient lightning, shadows, changing background) and vibrations while driving. As a result, the accuracy and performance of the system significantly decrease and hereby in consequence it affects the output of recommendations capable to avoid an emergency situation.

Experiments with the offline dangerous state related to high pulse rate recognition have been conducted for the same person in a relaxed state and after physical exercises. The experiments show that the proposed approach does not provide possibilities to determine the exact pulse but it is possible to predict if the person has a normal pulse or he/she has a high pulse rate with a certain probability that depends on several factors such as camera quality, lightness level, motions level of the head. Fig. 8 shows experiment results conducted with the same person with the similar light conditions. It can be seen that the calculated normal state (dash line) is mostly less than the increased pulse state (continuous line) but sometimes errors occurred. Authors also made experiments that show the results of impossibility to distinguish a normal state and an increased state. However, cameras of the modern smartphones

TABLE IV
EXPERIMENT STATISTICS PARAMETERS FOR PARTICIPATING DRIVERS

Characteristic	Driver 1	Driver 2	Driver 3	Driver 4	Driver 5	Driver 6	Driver7	Driver 8	Driver 9	Driver 10
Distraction state count	53	127	2	9	33	4	3	28	12	45
Drowsiness state count	41	15	8	0	8	15	1	22	19	3
Driving time (min)	79.60	50.75	4.82	3.43	21.40	6.93	92.48	18.56	11.45	22.50
Distraction per minute	0.67	2.50	0.42	2.62	1.54	0.58	0.03	1.51	1.05	2
Drowsiness per minute	0.52	0.30	1.66	0.00	0.37	2.16	0.01	1.18	1.66	0.13

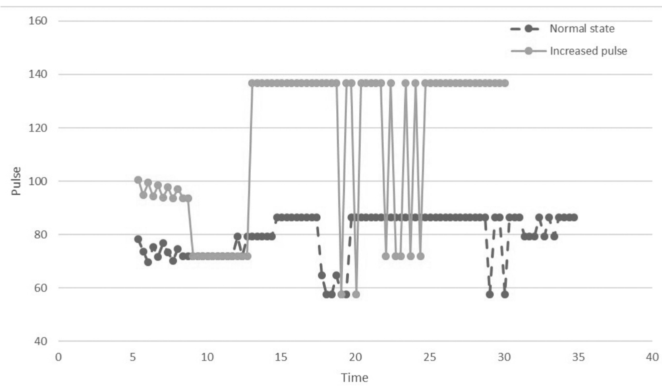

Fig. 8. Experiment 1 for a person in normal state and state with increased pulse rate.

are improving every year and it seems that using a modern smartphone should increase the accuracy pulse determination.

To identify the type of devices that are acceptable for the system utilization the following experiment has been conducted. Average dangerous state determination time has been calculated for the following list of devices. The list includes all main types of devices: the flagships such as Xiaomi MI5, Google Pixels 2 XL, Samsung Galaxy S8; devices with average performance; and low performance devices (see Fig. 7). The experiment shows that flagships and mid-range devices are applicable for the dangerous state identification. These devices supports dangerous state determination for 1.5 seconds that is applicable for considered case.

V. CONCLUSION

We presented a methodology to determine unsafe driving behavior by using a front-facing camera and sensors of a personal driver's smartphone. Distraction and drowsiness are two online types of unsafe driving behavior causing accidents on public roads that are recognized in the paper. High pulse rate is the offline dangerous state that is determined by a smartphone. Based on the information about high pulse rate, the following dangerous states can be recognized in according to the proposed scheme of smartphone utilization for dangerous states identification: drunk driving, aggressive driving, and stress condition. Authors plan to recognize these dangerous states in the future. We implemented the system for Android OS mobile devices and published it to the Google Play Store.[5] Drivers can use our system to enhance their driving safety and decrease accident probability. Taxi and logistic companies can use the system to track their drivers, asset location, dangerous states in real time. Insurance companies could use the system to monitor customers' driving and provide discounts for "safe drivers".

Several volunteers (from Russia, Sweden, and Japan) evaluated the system in real-time on public roads. We collected and analyzed statistical data of mobile application and their subjective opinions on dangerous states while driving using the human-computer interface based on speech recognition. The drivers confirmed that the mobile application determines dangerous states correctly in most cases.

In future work, we plan to personalize algorithms using driving statistics from cloud services. Algorithms will cluster drivers to groups, generate custom recommendations and calibrate parameters automatically with driver behavior (e.g. head rotation, percentage of eye closure). This will allow to increase the adaptability of the system for the particular driver.

ACKNOWLEDGMENT

The experiments on determining dangerous situation detection time (described in Section IV. Implementation) have been conducted in SPIIRAS due to the Russian State Research # 0073-2019-0005.

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