Dangerous Situations Determination by Smartphone in Vehicle Cabin: Classification and Algorithms

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Abstract—Nowadays smartphones are widely used in people daily life as they have a lot of sensors that can recognize physical conditions and people in their tasks. One of the task that a smartphone can be utilized is the driver face analysis in vehicle cabin. Together with the information from smartphone sensors such analysis allows to provide recommendations for a driver to prevent the emergency situations. The paper contains the classification of dangerous situations that can be determined by a smartphone as soon as algorithms that can be used for this determination.

I. INTRODUCTION

Nowadays smartphones becomes more and more engaged in people everyday life. Sensor and cameras allows to track the situation around the person and connection to the Internet provides possibilities of information search and utilization as soon as distributed computation utilization.

Traffic accidents in public roads are increased every year in most of countries in the world. Such situations as driver drowsiness and distraction as soon as aggressive driving, driving in stress condition, drunk driving and etc. increasing the probability of accidents, collisions between vehicles in the roads, damage of roads, and eco-friendly driving.

Last year's there are a lot of systems developed aimed at driver monitoring, dangerous states recognition and him/her notification based on dangerous behavior. Research and development community propose the hardware systems that are integrated to the vehicles and use the special sensors and driver monitoring; and applications for smartphones that use the existing hardware that usually driver has. The quality of the first solution is better but usually such systems are built in to the luxury vehicles and are expensive for the mass drivers. The goal of the following paper is to classify the dangerous states that can be determined in vehicle cabin based on the driver monitoring by built in smartphone sensors and camera mounted in the vehicle windshield and to study algorithms that is used for these purposes.

The scientific novelty of the paper is as follows:

- the list of parameters that can be acquired from smartphone sensors for dangerous situations determination;

- classification of the dangerous states: online, semi-online, and offline;
- algorithms for drowsiness, distraction, stress level, and high pulse rate determination;
- implementation and experiments with high pulse rate determination algorithm.

The paper is structured as follows. Section II describes the related work in the area of dangerous situation determination algorithms. The developed dangerous situation classification is presented in section III. Algorithms for dangerous state determination are presented in Section IV. Experiments are described in Section V. Main results are summarized in the Conclusion.

II. RELATED WORK

The authors of the paper [1] are presented an approach to study the behavior of truck drivers (that leads to excessive use of fuel) based on recorded the values of the speed sensors, engine revolutions per minute, fuel use. The proposed by authors RTI+ algorithm was used to determine this behavior. An approach was tested on the scenario aimed to determine excessive use of fuel: the car accelerates too quickly. Speed, fuel and engine sensors were used to determine driver behavior.

The authors of the paper [2] developed an algorithm for classifying the behavior of drivers at road intersections based on real data. The object of the study is the reaction of drivers to the prohibitory signal of the traffic light (red or yellow), as well as whether they stop in front of the stop line, or leave for it at a distance of 3 meters. When the potentially dangerous behavior of a driver is recognized the system should notify him/her about it. For dangerous behavior recognition, onboard vehicle sensors are used. For classification of drivers into "violators" and "docile", the Support Vector Machine (SVM) was used, and the Hidden Markov Model approach (HMM) was used to model the basic patterns in the set of observations. To collect data at the intersection, a real-time data collection system has been used. This system included four radar units that identified vehicles, measured vehicle speed, range and lateral position, a GPS antenna, four video cameras, and a traffic analyzer to record the phase of a traffic light.

In the study [3] the possibility of using vehicle inertial sensors from a CAN bus was studied. For the experiments authors use Volkswagen Passat vehicle. It is equipped with the appropriate sensors and "vision system". In particular, the sensor package includes: frontal radar, vehicle CAN signals, GPS, and front / rear camera. To study the behavior of drivers, all types of maneuvers were presented using three types of events: braking, acceleration and turning. The SVM algorithm was used by authors to analyze the data set in the study.

The authors of the paper [4] approves that the driving style can be divided into two categories: "typical" (non-aggressive) and aggressive. To increase driver awareness and safety, authors proposed a system that uses Dynamic Time Warping (DTW) and a smartphone based on sensors (accelerometer, gyroscope, magnetometer, GPS, camera) for detecting, recognizing and recording driver actions without external processing. The developed system is called "MIROAD" (Mobile-Sensor-Platform) and is used for intelligent recognition of aggressive driving. The HMM and DTW algorithms were used by authors to analyze the data.

In the study [5] authors explored ways to reduce the effect of stress on driver behavior. The study assessed the impact of adaptive signal control technology (ASCT) on stress levels and driver behavior. The participants of the experiment drove along two roads, one of which was equipped with ASCT, and the other was not. During the trip, system fixed data on the heart rate of drivers and their behavior. The data were analyzed using correlation coefficients of analysis of variance. As a result, it was found that on the road equipped with ASCT, the heart rate of drivers was significantly lower (about 10 beats), which led to a decrease in the latter's stress.

The authors of the paper [6] proposed the original Internet of Things module to protect people from deaths caused by traffic accidents due to drunk driving. The proposed system uses the device Raspberry Pi3 B (single-board computer the size of a bank card). It includes a touch sensor, alcohol concentration detection sensor, face detection, heart rate measurement. It also used the GPS module, emergency notification and automatic ignition shutdown.

In the study [7], authors proposed a highly efficient system that helps the driver to detect and warn in advance about dangerous maneuvers of vehicles caused by aggressive driving or DUI. System uses smartphone build-in sensors accelerometer and an orientation sensor. The program on a mobile phone calculates the accelerations based on the sensor readings and compares them with the typical unsafe driving characteristics obtained from actual driving tests.

In the paper [8] a new driving behavior recognition system based on a specific physical model and motion sensing data was considered to improve traffic safety. The system uses a nine-axis motion sensor that includes a three-axis accelerometer, a three-axis gyroscope and a three-axis magnetometer. To extract data authors used a Kalman filter and an adaptive time window. Based on the extraction function, various classifiers are performed to recognize different types of driving. The system classifies a normal driving behavior and aggressive driving behavior based on

such characteristics as accelerating, braking, changing lanes, and turning with high accuracy of 93.25%.

The authors of the paper [9] developed a system for monitoring driver drowsiness in real time. The system uses a smartphone camera to record the video of the driver face. The system fixes Facial landmarks on the detected face and subsequently calculates the proportions of the eyes, the mouth opening ratio and the ratio of the length of the nose. Depending on the calculated values the system detects a state of drowsiness based on selected adaptive threshold values, the system detects a drowsiness based on selected adaptive threshold values. The SVM and Histogram of Oriented Gradients (HOG) algorithms were used by authors to analyze the data.

The authors of the paper [10] distinguish six types of abnormal behavior of drivers: weaving, swerving, side slipping, fast U-turn, turning with a wide radius, and sudden braking. Authors proposed a system that find out each type of dangerous movement using build in smartphone sensors: 3-axis accelerometer, 3-axis orientation sensor and a digital video recorder. To identify behavior patterns a SVM algorithm is used.

Authors of the paper [11] implement review of the existing systems that determine the states, the behavior of drivers with the help of sensors of smartphones. The paper lists the sensors that are commonly used (accelerometer, gyroscope, GPS magnetometer, camera, microphone). Some algorithms that help analyze data are also indicated: DTW, SVM, machine learning algorithms, including artificial neural networks, a decision tree, and HMM.

Authors of the paper [12] proposed the driver fatigue detection system (DFS), which monitors the driver and gives warning signals if the driver falls asleep at the wheel. The system is built into the smartphone. The camera is used to determine the following states: the definition of yawning, nodding head, movement of the eyelids. To analyze data authors used Haar-like classification cascades, pattern matching algorithm.

The authors of the paper [13] proposed a system that determines the driver's drowsiness in real time. This system is designed as an application for a smartphone with Android OS, uses a camera to detect the driver's face. The accuracy of detecting drowsiness of this system is estimated at 93.37%. The system works adequately in natural light and regardless of whether the accessories are used for the driver, such as glasses, headphones, or a cap.

In scope of the paper analysis the following characteristics have been identified. The correspondence of the considered systems with the characteristics is presented in Table 1. In the table "+" means that the system is satisfied to the characteristic, "−" means not and "0" that it is not possible to recognize.

- Aggressive driving detection
- Fatigue detection
- Drowsiness detection
- Stress level detection

- Drunken driving detection
- Use of magnetometer

- Use of accelerometer
- Use of orientation sensor

TABLE I. COMPARISON OF THE CONSIDERED SYSTEMS

Article /comparison criteria	Aggressive driving detection	Fatigue detection	Drowsiness detection	Stress level detection	Drunken driving detection	Use of magnetometer	Use of accelerometer	Use of orientation sensor	Use of camera	Use of GPS	Use of speed sensor	Use of gyroscope	pulse measurement	Use of microphone	SVM algorithm	HMM algorithm	DTW algorithm	HOG algorithm	Haar-like classification cascades	Pattern matching algorithm
[1]	+	-	-	-	-	-	-	-	-	-	+	-	-	-	-	-	-	-	-	-
[2]	+	-	-	-	-	-	-	-	+	+	-	-	-	-	+	+	-	-	-	-
[3]	+	-	-	-	-	-	-	-	+	+	-	-	-	-	+	-	-	-	-	-
[4]	+	-	-	-	-	-	+	-	-	+	-	+	-	-	-	+	+	-	-	-
[5]	0	0	0	0	0	-	-	-	-	-	-	-	+	-	-	-	-	-	-	-
[6]	-	-	-	+	-	-	-	-	-	-	-	-	+	-	-	-	-	-	-	-
[7]	+	-	-	-	-	-	+	+	-	-	-	-	-	-	-	-	+	-	-	-
[8]	+	-	-	-	-	+	+	+	-	-	-	-	-	-	+	-	-	-	-	-
[9]	-	-	+	-	-	-	-	-	+	-	-	-	-	-	+	-	-	+	-	-
[10]	+	-	-	-	-	-	+	+	-	-	-	-	-	-	+	-	-	-	-	-
[11]	+	-	-	-	-	+	+	-	+	+	-	+	-	-	+	+	+	+	-	-
[12]	-	+	-	-	-	-	-	-	+	-	-	-	-	-	-	-	-	-	+	+
[13]	-	-	+	-	-	-	-	-	+	-	-	-	-	-	-	-	-	-	-	-

- Use of camera
- Use of GPS
- Use of speed sensor
- Use of gyroscope
- Pulse measurement
- Use of microphone
- SVM algorithm
- HMM algorithm
- DTW algorithm
- HOG algorithm
- Haar-like classification cascades
- Pattern matching algorithm

- Drowsiness
- Distraction
- Stress Level
- Aggressive Driving
- Drunk Driving

III. DANGEROUS SITUATION CLASSIFICATION

Related work review allows to highlight the parameters that are needed for dangerous situation determination algorithms and accessible for smartphone built in sensors (see Table 2). Based on these parameters the possibility of the following dangerous states determination have been identified:

It has been proposed to classify these dangerous states as online, semi-online, and offline (see Fig. 1). Online dangerous states have to be determined in real time while driving by smartphone. The determination time depends on the context situation (driver reaction time, vehicle speed etc.) but it is around two seconds. These dangerous states are drowsiness and distraction. If the driver is drowsy or distracted the system should influence to him/her in real time or an accident can occur.

Semi-online dangerous states are the dangerous state that can be detected in the process that takes more than two seconds but the should be determined by smartphone as soon as possible. Such dangerous are aggressive driving and pulse parameter that can be a dangerous in case of high values.

TABLE II. ACCESSIBLE PARAMETERS CLASSIFICATION FOR DANGEROUS SITUATION DETERMINATION

| Parameter	Sensor	Description
Eye opening ratio	Camera	The parameter is used to determine the drowsiness state by eyes
PERCLOS		
Mouth opening		The parameter is used to determine the drowsiness state by mouth
Tilt angle of head		The parameter is used to determine the drowsiness state by head
Rotation angle of head		The parameter is used to determine the distraction state by head
Pulse		The parameter is used to determine the driver pulse and stress level
Acceleration	Accelerometer	The parameter is used to determine the aggressive driving state by vehicle acceleration
Vehicle turn	Gyroscope	The parameter is used to determine the aggressive driving state by vehicle turning
Voice	Microphone	The parameter is used to determine drowsiness state
Light level	RGB-light sensor	The parameter is used to determine the light level that is influenced to the dangerous state determination using smartphone camera
Geolocation	GPS / GLONASS	The parameter is used to give a recommendation to driver where he can sleep id he falls asleep
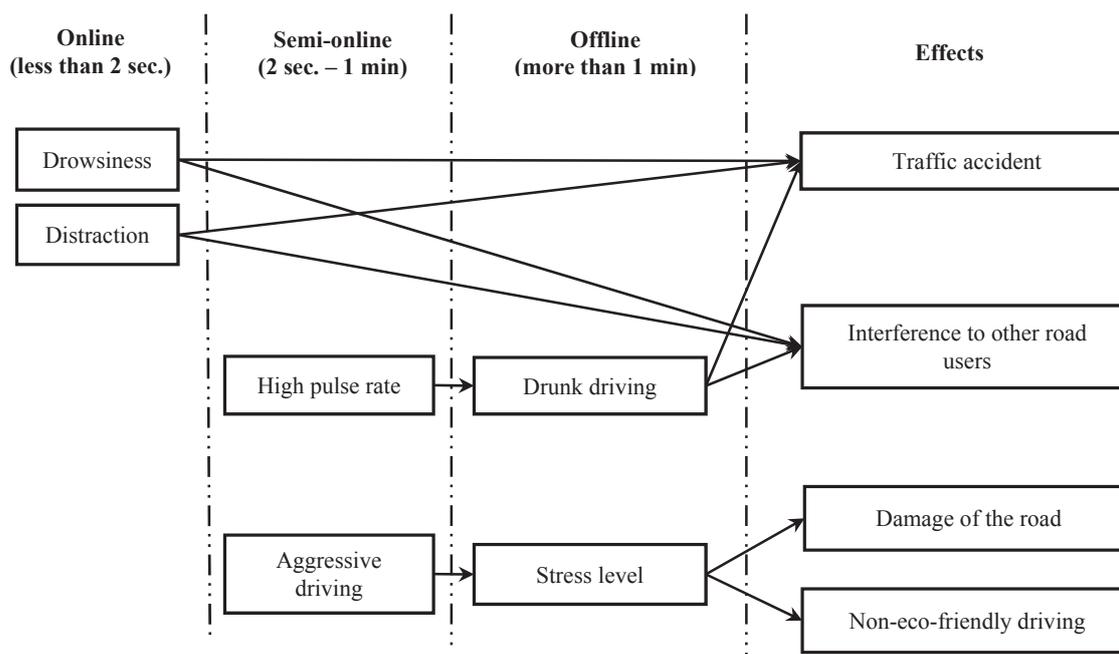
Fig. 1. Classification of the Dangerous Situations Determined based on Smartphone Sensors

Offline dangerous states are the dangerous states that are determined in the cloud (not in smartphone). The determination time can be much more than one minute since the calculations have to be implemented and a lot of data has to be analyzed. These situations are determined on the basis of not only the collected data in real time, but also previously collected, and stored. These dangerous states are: drunk driving and stress level.

There are following effects have been determined as a consequences of dangerous states: traffic accident, impediment to other road users, damage of the road, and non-eco-friendly driving.

Drowsiness is a state most susceptible to the drivers of long-distance buses, the night drives, as well as drivers of truckers. Characteristic features of drowsiness are: yawning, nodding his head, closing his eyes, blinking. To recognize these states usually a smartphone camera is used.

Distraction is a condition that is characterized by turning the driver's head to the side, in such a way that the driver does not monitor the condition of the road for some time.

High pulse rate is a state that is characterized by rapid heartbeat due to the impact of the external environment on the driver. This state allows to determine the state of drunk driving. A smartphone camera can be used to recognize the increased heart rate.

The stress level is a state of the driver, in which the external environment has a negative impact on the psycho-emotional driver state. This state can causes the aggressive driving. To determine the level of stress the gyroscope as soon as accelerometer sensors can be used.

Drunk driving is a state in which the driver's body contains alcohol in a certain concentration. The consequence of this condition is the manifestation of one of the types of aggressive driving. To determine drunk driving the following sensors are used: camera, gyroscope, accelerometer, GPS/GLONASS.

Aggressive driving is such a driver's behavior, which is characterized by weaving, swerving, side slipping, fast U-turn, turning with a wide radius, sudden braking. The following sensors are used to recognize this state: accelerometer, gyroscope, GPS, orientation sensor, magnetometer, camera.

IV. DANGEROUS STATE DETERMINATION ALGORITHMS

The section discuss the algorithms for following online and semi-online dangerous states determination based on smartphone sensors: drowsiness, distraction, aggressive driving, and high pulse rate. In the future authors are planned to develop the algorithms for drunk driving and stress level determination.

A. Drowsiness

In according to the literature drowsiness can be determined by the analysis of the following three parameters: the ratio of opening eyes (E), the ratio of opening mouth (M), the angle of the head (NA). Bellow an algorithm is proposed based on analysis of the related work. It consists of the following two steps: parameters calibration, drowsiness determination.

At the first step a number of frames are analyzed (some authors propose 300 frames). Based on these frames the parameters E, M, NA are determined and the threshold values are calculated: E_0, M_0, NA_0. At the second step the measurements of E, M, NA is implemented. During the measurement of indicators in real time, the state of drowsiness is based on the threshold values of E_0, M_0, NA_0.

The formula for calculation of the coefficients E and $E1$ for the left eye is presented below; the coefficient E for the right eye is calculated similarly.

$$E = \frac{(p2-p6)+(p3-p5)}{2(p4-p1)},$$

where [p1; p6], [p7; p10] – points on the left and right eyes necessary to calculate the eye opening ratio (see Fig. 2).

Fig. 2. Points detected by smartphone camera for monitoring drivers eyes

PERCLOS is a measure of drowsiness detection, which is called the percent closure of the eyelid over the pupil over time and reflects the slow closure of the eyelid, not blink. The definition formula is presented below, where N_m is the total number of frames taken per minute, N_a is the number of frames on which the eyes are open. Related work papers suggest that in case the PERCLOS parameter is more than 70% (parameter D in the algorithm scheme), then a state of drowsiness is revealed. The algorithm of determination drowsiness by eyes monitoring is shown on Fig. 3.
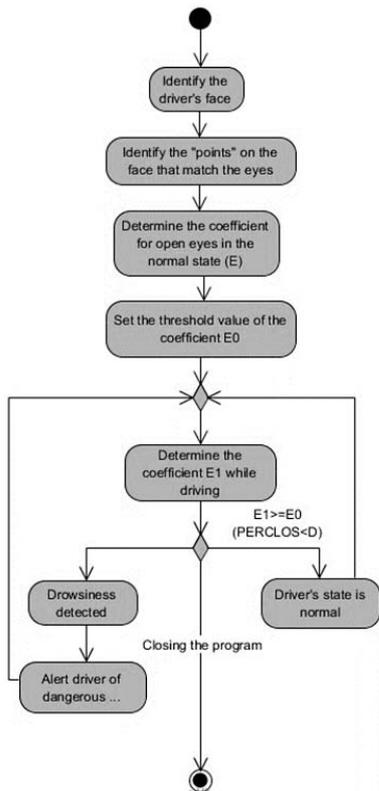

Fig. 3. Drowsiness determination algorithm by eyes monitoring

Fig. 4. Points detected by smartphone camera for monitoring drivers mouth
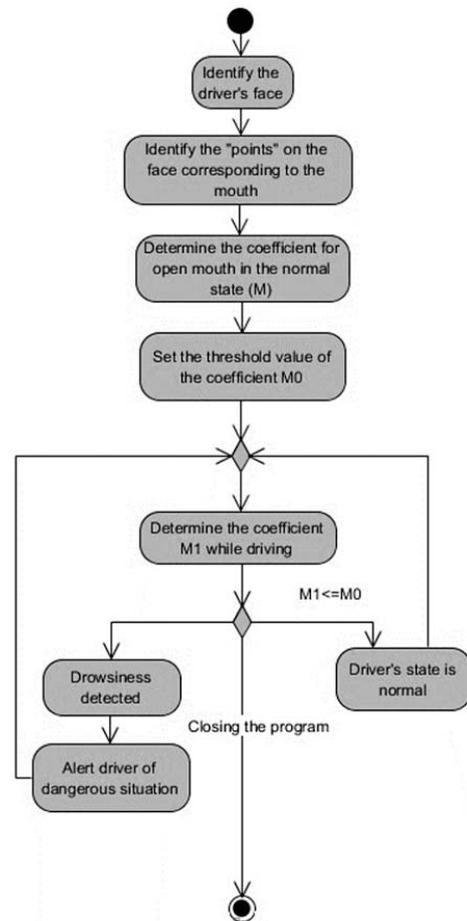
Fig. 5. Drowsiness determination algorithm by mouth monitoring
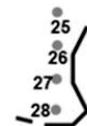
Fig. 6. Points detected by smartphone camera for monitoring drivers nose

Driver drowsiness can be determined also by the degree of mouth opening (yawning). Yawning can be defined as follows: if the mouth opening ratio M_1 increases monotonically and then tends to the value M_0, then this state is classified as yawning, therefore, as drowsiness.

The formula for calculating the coefficients M, $M1$ is presented below.

$$M = \frac{(p15 - p23) + (p16 - p22) + (p17 - p21)}{2(p19 - p13)}$$

$$PERCLOS = \frac{N_m - N_a}{N_m} * 100\%$$

where [p13; p24] – points on the mouth necessary to calculate the mouth opening ratio (see Fig. 4). An algorithm of determination drowsiness by mouth monitoring is shown on Fig. 5.
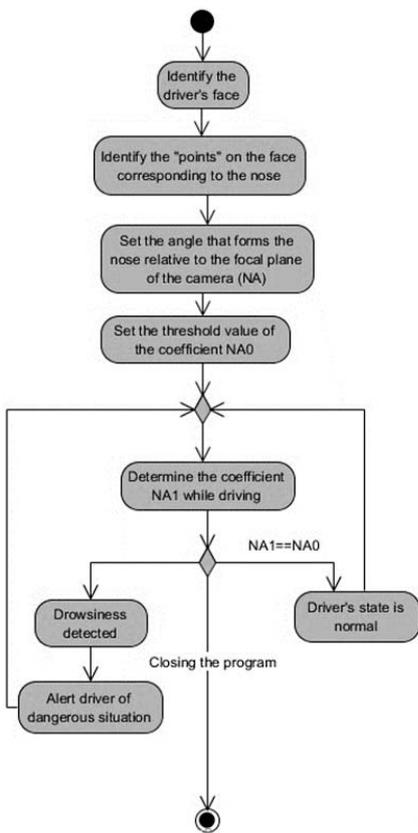
Fig. 7. Drowsiness determination algorithm by tilt angle of nose monitoring
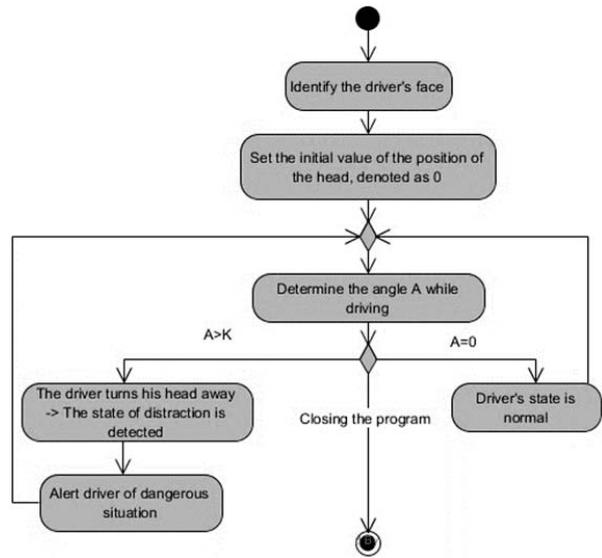
Fig. 8. Distraction determination algorithm by rotation angle of nose monitoring

The state of drowsiness can be also determined by the driver's head nods. The driver's head can either bend down or lean back. Firstly, the driver's nose angle has to be calibrated and further, if the driver begins to fall asleep, the angle changes up or down, thus revealing a state of drowsiness.

The formula for calculating the coefficients NA, NA_1 is presented below.

$$NA = \frac{nose\ length(p28 - p25)}{average\ nose\ length}$$

Fig. 9. Aggressive driving determination algorithm by monitoring vehicle coordinates

where [p25; p28] – points on the nose necessary to calculate the tilt angle nose (see Fig. 6). An algorithm of determination drowsiness by tilt angle of nose monitoring is shown on Fig. 7.

B. Distraction

Distraction dangerous state usually is determined by the left/right head angle measurement. Initially the head angle is calibrated like with situation with drowsiness determination. The angle A is the calibrated offset. The distraction dangerous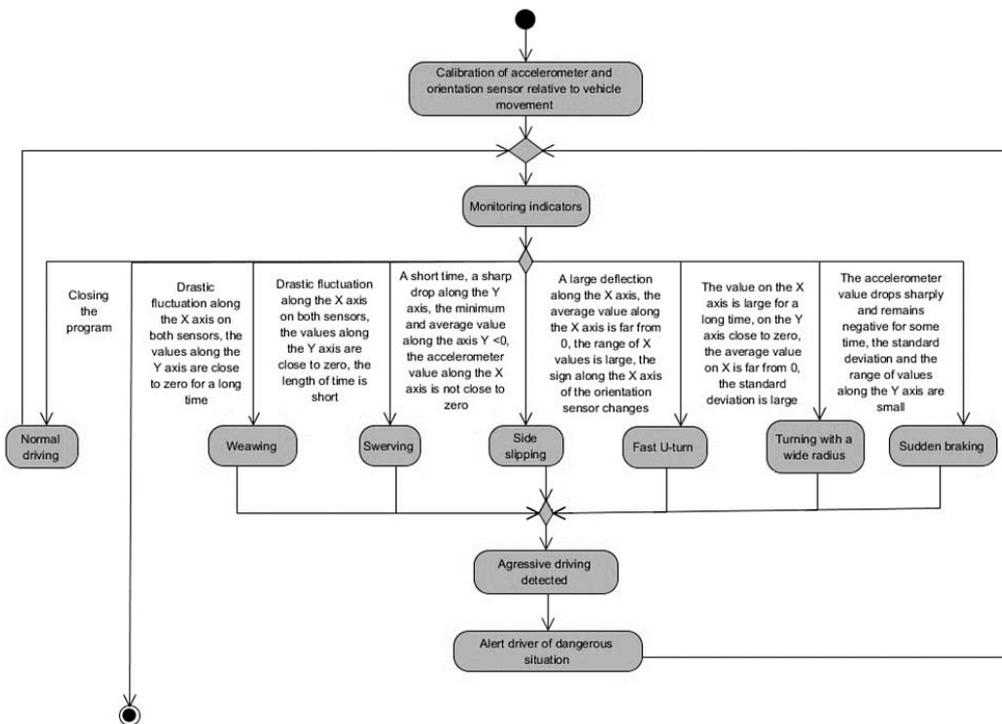 state is determined when driver turns his head more than an angle *K*. An algorithm of distraction determination by rotation angle of nose monitoring is shown on Fig. 8.

C. Aggressive Driving

The state of aggressive driving is determined using accelerometer and orientation sensor values and is classified into 6 types of behavior: weaving, swerving, side slipping, fast U-turn, turning with a wide radius, sudden braking.

Algorithm of determination aggressive driving by monitoring vehicle coordinates is shown in Fig. 9.

D. Pulse Determination

The analyzed research and development in the area of pulse detection by camera show that the main scheme looks like as follows. Face of the person is tracked, then the analyzing area is determined, mean color is calculated, and then transformed to the frequency that characterized the pulse. Fig. 13 shows two different algorithms for pulse detection implemented in the following applications: webcam-pulse-detector (https://github.com/thearn/webcam-pulse-detector) and motion-pulse (https://github.com/COMP6206-vision-based-pulse-detection/python-motion-pulse).

Both algorithms have the following structure: data extraction, artificial sample rate raise, frequencies extraction, drop abnormalities, and filter values that are not related to pulse steps.

Webcam-pulse-detector algorithm relies on color change in a region of user's face at step 1. Region of interest is user's is shown in the Fig. 10 by green rectangle. To extract the region of interests from face image the image should be recognized utilizing OpenCV, and the forehead region has to be cut from the face image for each frame in video. The region of interests 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. Mean value of those three numbers is the data extracted from the frame and it is added to data buffer [14] (see example in Fig. 11).

Motion-pulse algorithm uses the facial points movement to estimate pulse. Algorithm selects series of point on the face using OpenCV (Fig. 12) and utilizes feature tracking algorithm to track points' coordinates. Points' coordinates for every frame of the video are extracted [15].

Fig. 10. Person face and region of interest highlighted by a rectangle
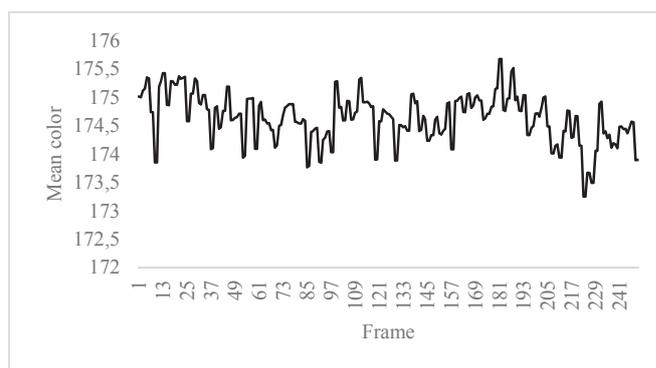

Fig. 11. Example of the mean color values got from region of interests

Fig. 12. Points in the person face tracked by the Motion-pulse algorithm

At the step 2 the interpolation of the results got after the step 1 is implemented. Since the smartphone camera has 30 frames per second rate, but electrocardiography devices record with sample rate of 250Hz it is needed to synchronize these values. Motion-pulse algorithm uses cubic-spline interpolation to 250 Hz. Since the frames per second rate is not constant Webcam-pulse-detector algorithm uses one dimensional linear interpolation to make intervals between frames even.

The 3rd step is aimed at drop abnormalities in the analyzing data. It presents only in motion-pulse algorithm. Recorded motions are not only pulse motions but also swallowing, adjustments in posture etc. To deal with them 25% of movements with highest amplitudes are dropped.

The goal of the step 4 is to convert the interpolated color data to the frequency. Before the conversion, the Hamming window function is applied (see example in Fig. 14).
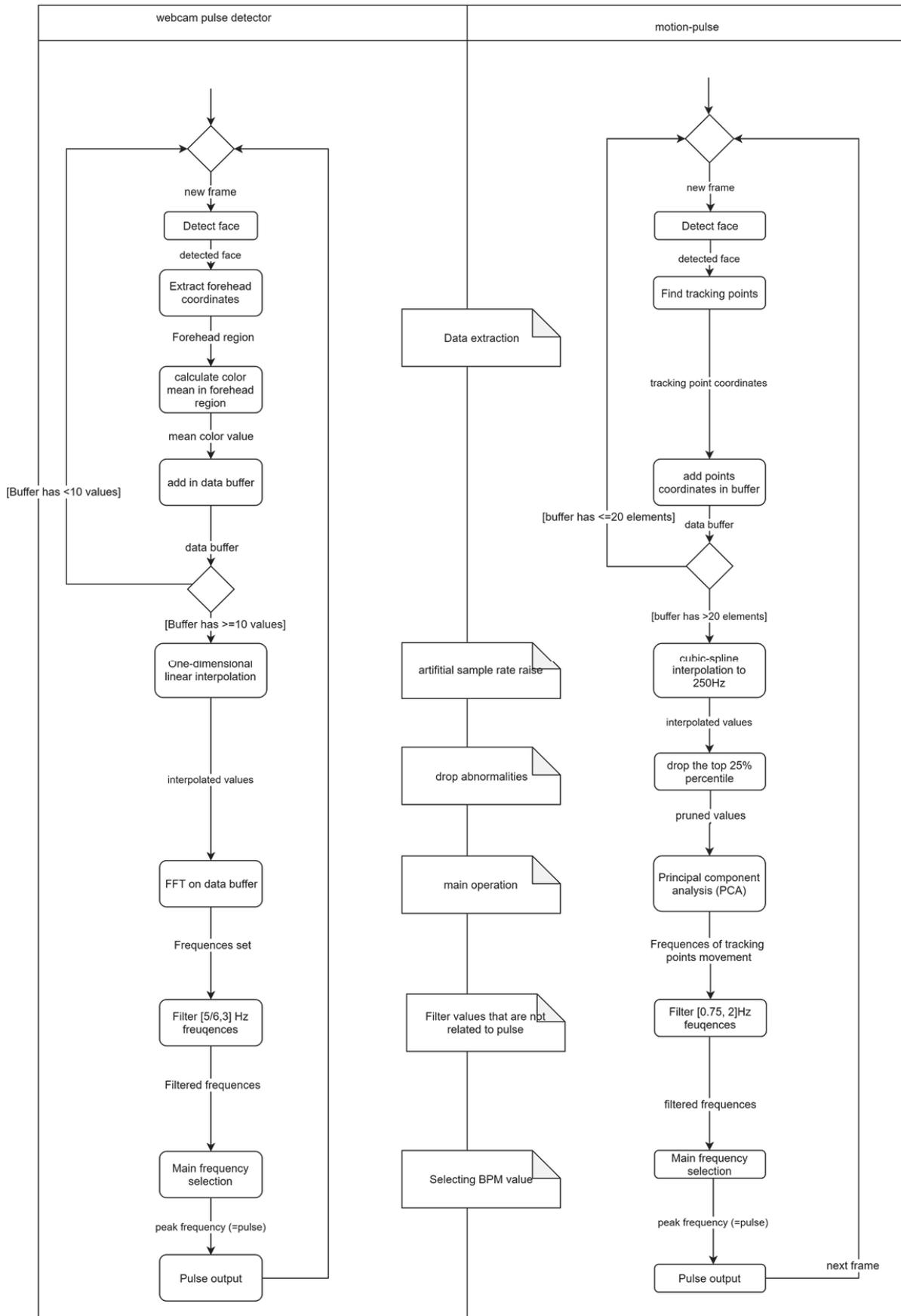
Fig. 13. Pulse determination algorithms based on information from smartphone front-facing camera measurements
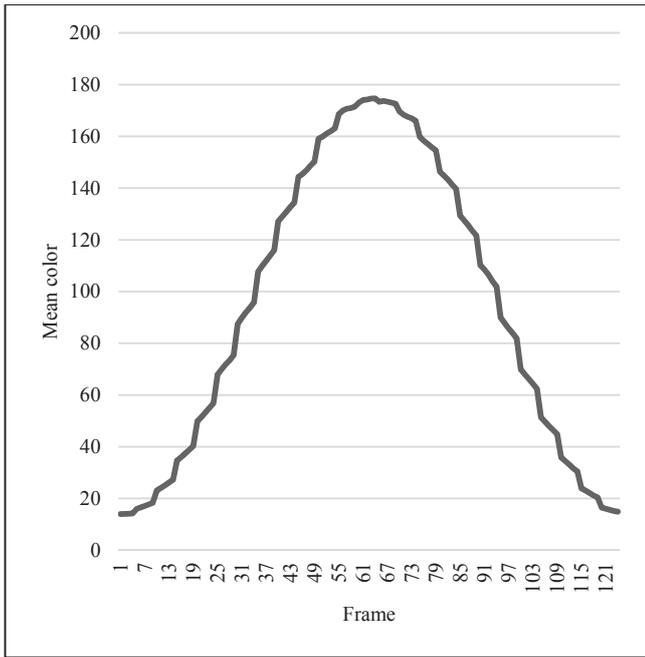
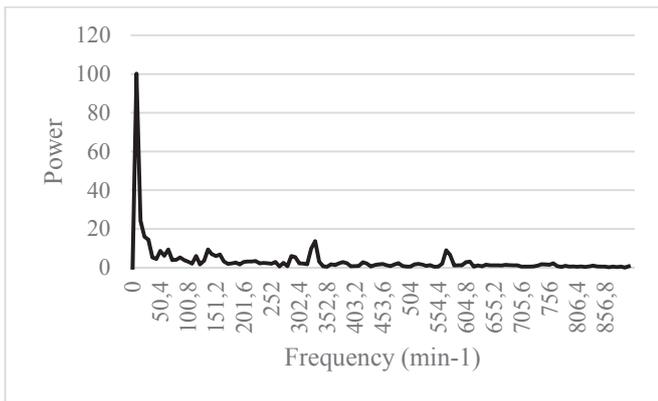Fig. 14. Example of the data with Hamming window applied

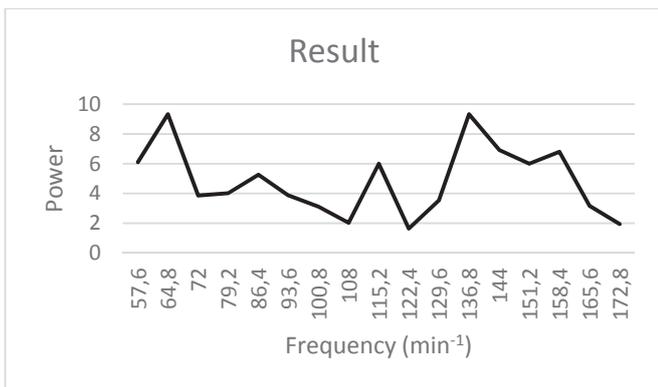Fig. 15. Example of the fast Fourier transforms

Fig. 16. Filtered data between 50 and 180 beats per minute

To implement the converting webcam-pulse-detector uses fast Fourier transforms [14] on interpolated data to determine the power and phase spectra (see example in Fig. 15). After the transformation, frequencies should be filtered, and the result is powers of all frequencies between 50 and 180 beats per minute (see Fig. 16). The highest of obtained frequencies

is considered as pulse estimation. Motion-pulse algorithm uses principal component analysis and select the component whose temporal power spectrum best matches a pulse using fast Fourie transformation (at the considered case it is 136.8 bpm).

At the step 5 received frequencies are being filtered. Pulse values have rather certain limits and values outside those limits should be filtered. In webcam-pulse-detector limits are [50, 180] beat per minute, in motion-pulse algorithm limits are [45, 120] beats per minute.

In the final step resulting pulse value is being selected. From the filtered values pulse estimation is frequency with the highest power.

IV. EXPERIMENTS

The presented algorithms have been tested for prepared in advance video fragments captured by Xiaomi Redmi 4 Prime smartphone camera for the same person in calm state and after the physical excesses. The experiments show that the proposed approach does not provide possibilities to determine exact pulse but it is possible to predict is the person has a normal pulse or he/she has increased pulse with a certain probability that depends on the several factors such as camera quality, lightness level, motions level of the head. Fig. 17 and Fig. 18 show experiments conducted with the same person with the similar light conditions. It can be seen that calculated normal state (dash line) mostly less than increased pulse state (continuous line) but sometimes errors are occurred. Authors also got experiments that shows the results that shows impossibility to distinguish normal state and increased state. However the cameras of the modern smartphones are developed every year and seems that using the modern smartphone should increase the pulse determination successfulness.
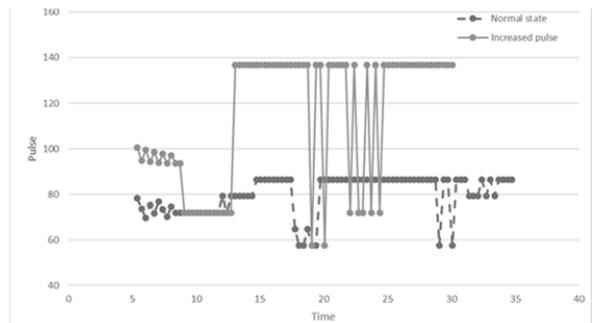

Fig. 17. Experiment 1 for a person in normal state and state with increased pulse rate
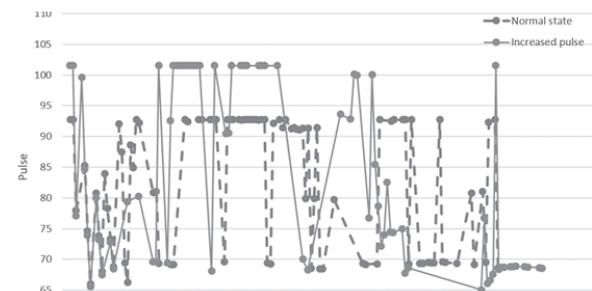

Fig. 18. Experiment 1 for the same person in normal state and state with increased pulse rate

VII. CONCLUSION

The paper presents a classification of the dangerous states that can be detected in the vehicle cabin using smartphone camera and sensors as soon as the list of parameters that shoud be tracked by mobile phone. There are four algorithms have been considered: drowsiness, distraction, aggressive driving, and pulse determination. Drowsiness and distraction dangerous states have been implemented in the developed by authors DriveSafely application accessible in Google Play market (https://play.google.com/store/apps/details?id=ru.igla.drivesafely&hl=ru). The presented pulse determination algorithm has been evaluated based on videos captured by smartphone for a person in normal state and in state with increased pulse after the physical exercises. Experiments show that usually it possible to determinate that a person has an increased pulse but it is not possible to determine the exact value of the pulse rate. It should be noted that increased pulse determination is important not only for the vehicle driver but also for e-bikes [16].

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