Smartphone-Based Identification of Dangerous Driving Situations: Algorithms and Implementation

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Abstract—**In this paper, we demonstrate the concept of the situation analysis of dangerous driving events for smartphones to fully understand the driving situation in a given scenario in a real time and to undertake actions necessary to avoid road accidents. To fulfil these, we utilize a wide array of sensors for creating a consistent and extendable description of most common dangerous situations, a situation model and situation analysis. In the situation model, on-board smartphone sensing signals are used to build up a representation of the environment around and within the vehicle. On top of the situation model, a situation analysis is established to detect driver hazards, according to the given description of the driving situation, and provide a driving strategy to prevent such dangerous situations. The paper describes the details of the algorithms, following by simulation results, which show the feasibility of the proposed algorithm.**

I. INTRODUCTION

Research and development of advanced driver assistance system (ADAS) is a hotly debated topic. Throughout the last decades, the number of road accidents remains high. According to road traffic accidents statistics, ninety percent are caused by human errors [1].

A way to implement the advanced safety solution is a mobile application for smartphones that detects dangerous situations and alerts the drivers. There are many mobile applications that are aimed at implementing driver assistance while driving; the analysis of these applications is presented in [2]. It is important to highlight that analyzed mobile applications are concentrated on the dangerous situations that may occur only outside of the car and do not take into account the situations observable inside the car.

Most modern smartphones are not only a combination of telephone and computer; they also come with a variety of built-in sensors such as accelerometer, gyroscope, ambient light sensor, proximity sensor, magnetic field sensor, and GPS, that are capable of measuring some physical quantity and converting it into a signal. These sensors provide raw data with high precision and accuracy for measuring the respective sensor values. For example, gravity sensor can be used to track gestures and motions, such as tilt, shake and so on. Similarly, geomagnetic sensor can be used to track the compass bearing. Accelerometer can be used for estimating rate of speed change. These sensor data are used for recognizing unsafe driver manoeuvres. At the same time, smartphones are also equipped with front-facing and rear-facing cameras giving an opportunity to track the driver behaviour and road conditions relatively. Smartphones are able to generate alerts for a driver with the help of vibration, audible signal or visual information.

The most commonly occurring dangerous driving events we focus on are drowsiness (strong desire for sleep), distraction (e.g., when the driver is distracted and takes their eyes off the road), irritability, careless lane change and tailgating (i.e., getting too close to the car in front). With exception of irritability, all other driving events had been taken from [3]. These unsafe dangerous events are classified into two groups in terms of the context that are in-car pipeline and road pipeline.

We propose algorithms for mobile application that can alert drivers before they perform a dangerous manoeuvre in order to avert road accidents.

This paper extends the research work presented in [4]. In this study, we address the problem of anticipating maneuvers that a driver is likely to perform in the next few seconds, describe algorithms for detecting dangerous events and alert driver by displaying an attention icon on the phone's touch screen along with an audible alert.

The rest of the paper is structured as follows. Section II overviews the dangerous road events. Section III presents algorithms for determining unsafe road situations that could lead to road traffic accidents. The implementation details of ADAS mobile system are presented in Section IV. Main results and findings are summarized in Conclusion.

II. OVERVIEW OF DANGEROUS EVENTS

A. In-car pipeline

Drivers are faced with a variety of road hazards and an increasing number of in-car distractions (e.g., music, eating and drinking, talking to passengers, phone calls, navigation systems, smartphone texting and browsing, etc.). The front camera of the smartphone is used to monitor the driver. It is designed for tracking facial expressions and gestures of the driver. First of all, the system is configured to initially detect eyes closure, responding with a warning signal. Simultaneously, the system analyses the driver's eye-blink rate, recognizing the difference between just blinking and closing of the eyes while driving.

1) Drowsiness: Drivers who have symptoms of fatigue are prone to episodes of micro sleep [5]. Drivers are often unaware of these episodes; rather, people typically think they have been awake the whole time or have lost focus momentarily. As a result, drivers experiencing bouts of micro sleep are at high risk of having an accident.

2) Distraction: Maintaining eye contact with the road is fundamental to safe driving. The National Highway Transportation Safety Administration (NHTSA) has defined distracted driving as “an activity that could divert a person’s attention away from the primary task of driving”. Distraction occurs when drivers divert their attention away from the driving task to focus on another activity instead.

3) Irritability: Driver’s irritability can lead to aggressive driving behaviour. Driver’s anger also leads to aggressive driving behaviour [6]. These include behaviours such as excessive speeds, inappropriate over-taking or lane changing, weaving in and out of lanes, following other drivers too closely and rude or offensive communications with other drivers [7].

B. Road pipeline

The road classification pipeline is based on the use of rear-facing camera able to recognize road marking, vehicle position in its lane and following distance estimation subsequently.

1) Tailgating: Drivers are guilty of tailgating when they are following the vehicle in front of them too closely and not allowing enough room to brake in an emergency without a collision. The driver should know the correct distance at which they should follow a vehicle. Most recommended is the two second rule [8] in which a driver picks a fixed point and one the vehicle in front of them passes the chosen point they should begin counting, they’re own vehicle should pass the fixed point two seconds after the vehicle in front of them. If your vehicle reaches that point faster than that you should try to increase the distance.

2) Careless Lane Change (CLC): An improper or erratic traffic lane change is a serious traffic violation. It occurs when a driver moves a vehicle from its lane without first making sure that the lane changing manoeuvre can be done safely.

Dangerous driving events only relevant to the in-car pipeline will be discussed further below.

III. ALGORITHMS

A. Detection of Dangerous Events

The composite diagram for the dangerous driving events recognition is presented in the Fig. 1. It describes the detection of following unsafe road situations such as drowsiness, distraction, tailgating and CLC. Each of these situations is based on the use of combinations of various indicators giving us measurements of mental states in real time. In order to anticipate manoeuvres, we reason with smartphone sensing information and the contextual information from the surrounding events, which we refer to as the driving context. We obtain this driving context from multiple sources, like as smartphone’s cameras and sensors:

- Front-facing camera videos of the driver inside the car.
- Rear-facing camera videos of the road in front.
- Accelerometer.
- Gyroscope.
- Global position coordinates (GPS).
- Street maps.

From this we extract a time series of multi-modal data from both inside and outside the vehicle.

1) Drowsiness: The smartphone’s front camera monitors the head movements, facial expressions and the prolonged and frequent blinks indicative of micro sleep.

Existing research findings have shown that the percentage of closure of eyelid (PERCLOS) is an effective indicator for evaluating a driver’s drowsiness. A measure of drowsiness, PERCLOS, was generated and associated with degradation in driving performance in a simulated roadway environment. PERCLOS formally represents the proportion of time within one minute that eyes are at least 80% closed [9]. This driver state information such as PERCLOS and eye-blink speed is provided by smartphone’s front-facing camera. We continuously compute PERCLOS and declare the driver “drowsy” if PERCLOS exceeds a threshold (28%) [10].

Another parameter is the speed of blinking, giving a permissible range of 0.5–0.8 seconds per blink.

One more indicator of drowsiness is a yawning. If the driver makes more than 3 yawns in 30 minutes, we consider the driver is in the dangerous state.

And finally, the fourth indicator of this dangerous event is the head nodding. If the number of head tilts exceeds a threshold (4) in 2 minutes, the drowsiness is inferred.

2) Distraction: Two types of inattentive driving are monitored. In the first type, the output of the face direction classifier based on head movements and head position is tracked.

If the driver’s face is not facing forward for longer than three seconds while the car is moving forward (i.e., 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. In the second type, we trace a vehicle movement and determine whether the vehicle made a turn or not. We recognize four driver’s face related categories that include: (1) no face is present; or the driver’s face is either (2) facing forwards events, towards the road; (3) facing to the left events (i.e., a $\geq 15°$ rotation relative to facing directly forward); and, (4) facing to the right events (another $\geq 15°$ rotation but this time to the right). Each time a turn is detected the historical output of the face direction classifier is checked. If there is no head turn corresponding to a car turning event then the driver did not check that the road is clear before turning – as a result, a dangerous event is inferred.

3) Tailgating: The smartphone’s rear camera monitors the distance between cars to determine if the driver is too close to the car in front. We adopt the calculation for a minimum following distance, which relies on the speed estimation and

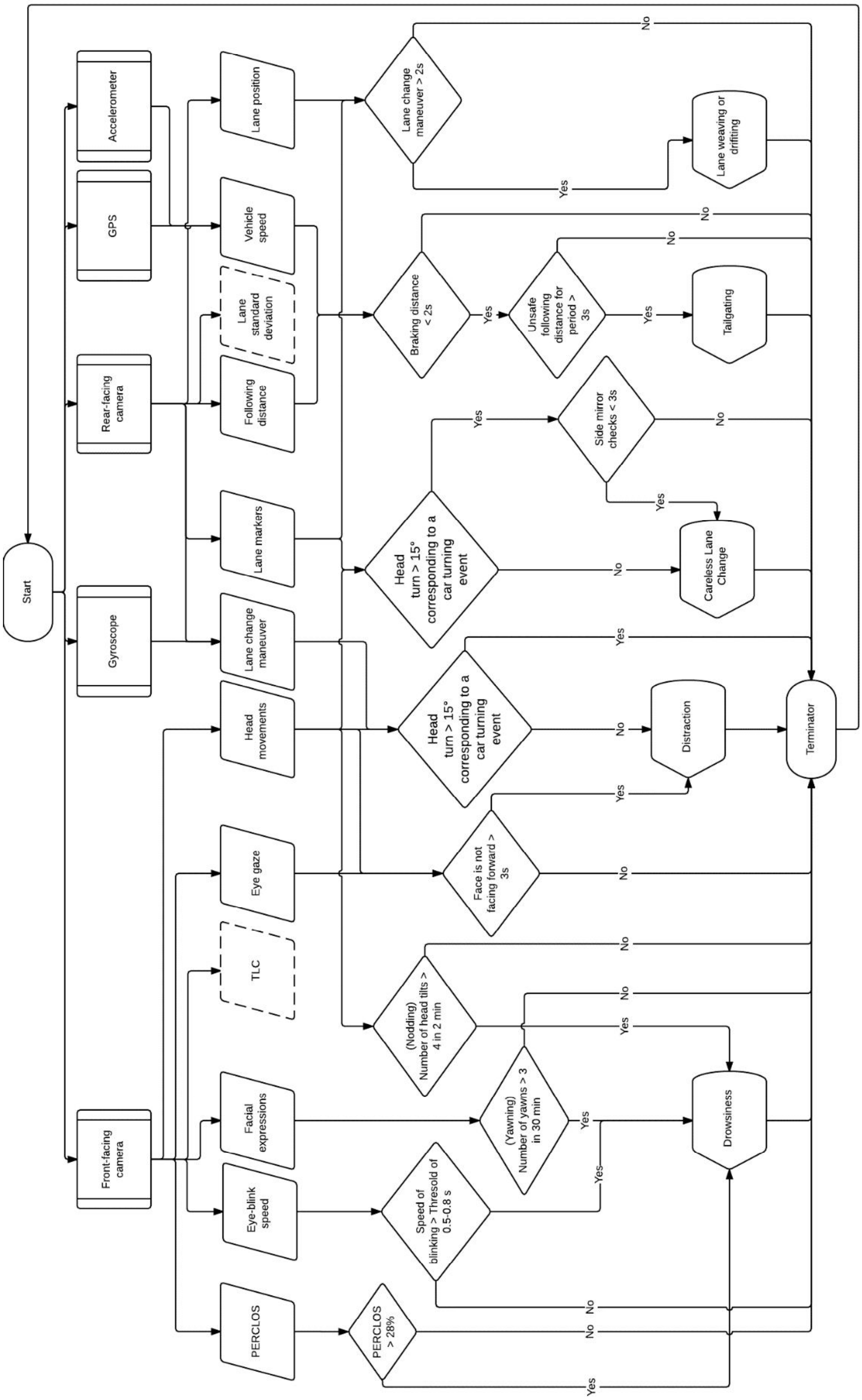

Fig. 1. The diagram of dangerous events recognition

the recognition of the following vehicles. A “safe following distance” is a distance the driver should ideally stay at least 2 seconds behind any vehicle that is directly in front of the driver's vehicle. If we determine the safe following distance is not respected for a period longer than 3 seconds a dangerous driving event is inferred.

4) Careless Lane Change (CLC): The trajectory classifier based on the lane markers and lane position of the driver’s car should monitor two types of unsafe lane changes. In first type, one or more erratic lane changes the driver performs are tracked. If the classifier infers lane changes continuously for longer than 2 seconds, which is significantly longer than the typical duration of a lane change manoeuvre, dangerous driving event is raised.

In the second type, the trajectory classifier checks that the driver performed side view mirrors checks for cars before the lane change. Executing lane changes safely also requires a driver to check blind spots before proceeding. The driver does this by looking in the side and front mirrors of the car to check for unexpected vehicles. Each time the trajectory classifier determines a lane change event has occurred the recent inferences made by face direction classification are examined. If there is no corresponding head turn to a lane change event and the duration of mirror checks is less than 3 seconds, occurring prior to the lane change event detection, then a dangerous driving event is inferred.

A. Notification of the driver about dangerous situation

An individual driver behavioural strategy is proposed for each dangerous event to avoid. Considering the smartphone’s capabilities the driver’s ability to perceive alerts can be presented as follows:

- Signalling tune or/and voice of the alert;
- A vibration of the smartphone device;
- An alerting icon on the screen of the phone;
- A textual message on the alerting message.

General countermeasures to prevent a dangerous road situation while driving are to stop driving, take a nap or drink a caffeinated beverage. Short 15-20 minutes naps can improve well-being, performance and short-term alertness. 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 drink can promote short-term alertness. It takes about 30-40 minutes for caffeine to enter the bloodstream.

It should be noted that the impact on a driver’s dangerous state of driving is determined not just by the type of state, but also the frequency and duration of the task.

1) Drowsiness: If the mobile application detects drowsiness, the application alerts the driver by playing a signal tone and checks whether there are any cafes or hotels close by a driver.

If the driver is on the country roads, the application suggests driver to take a rest through the distance of 100 kilometers. Otherwise, if driver goes through the city, the observable distance of rest spots is limited to 20 minutes of driving. If a place for power nap is found, the application will route to the nearest one to drink a cup of coffee. If there are no hotels neither cafes, it will recommend the driver to listen to music, talk to passengers without being distracted, cool the car interior, sing the driver yourself or pull over and take a nap. The flowchart of the drowsiness state is presented in the Fig. 2.

2) Distraction: There is a diversity of distraction tasks that can affect driver in different ways. Driver distraction is a contributing factor in many crashes. If the application detects the driver’s distraction, the application alerts the driver by playing a voice recording, a warning tone and flashing the smartphone’s screen. This algorithm considers three types of distracted driving the driver most likely can face during the trip. Firstly, the application will check whether the driver is talking to passengers and if the condition is true, it will play a warning tone. If the driver is fond of listening to music or radio, the system will recommend the driver to turn off the music. Finally, if the driver adjusts the multimedia system, the application will play a warning tone. For all cases, the mobile application will play a warning tone and flash the smartphone screen. The overall scheme of distraction state avoidance is presented in the Fig. 3.

IV. IMPLEMENTATION

The implementation of proposed mobile ADAS system has been developed for Android-based mobile device. Evaluation has been done for the multi-core Lenovo K910L Android smartphone. The driver and vehicle classification pipelines, which represent the most computationally demanding modules, are written in C and C++ based on the open source computer vision library (OpenCV library) and interfaced with Java using JNI wrappers. The details can be found in [4].

Currently, using the front-facing camera our mobile application is able to recognize only two dangerous events, like as drowsiness and distraction.

A Mobile Vision Google API [11] is used that provides the well-optimized Android framework for finding objects in photos and videos. The framework includes detectors, which locate and describe visual objects in images or video frames, and an event driven API that tracks the position of those objects in video.

The face recognition process includes following key steps:

- The creation of the face detector.
- Face detection and face tracking.
- Facial landmarks detection like as “left eye”, “right eye”.
- Facial characteristics classification like as “eyes open”, “eyes close”.

To provide the functionality for face detection in consecutive video frames the Face API is used and Classification API that is determining whether a certain

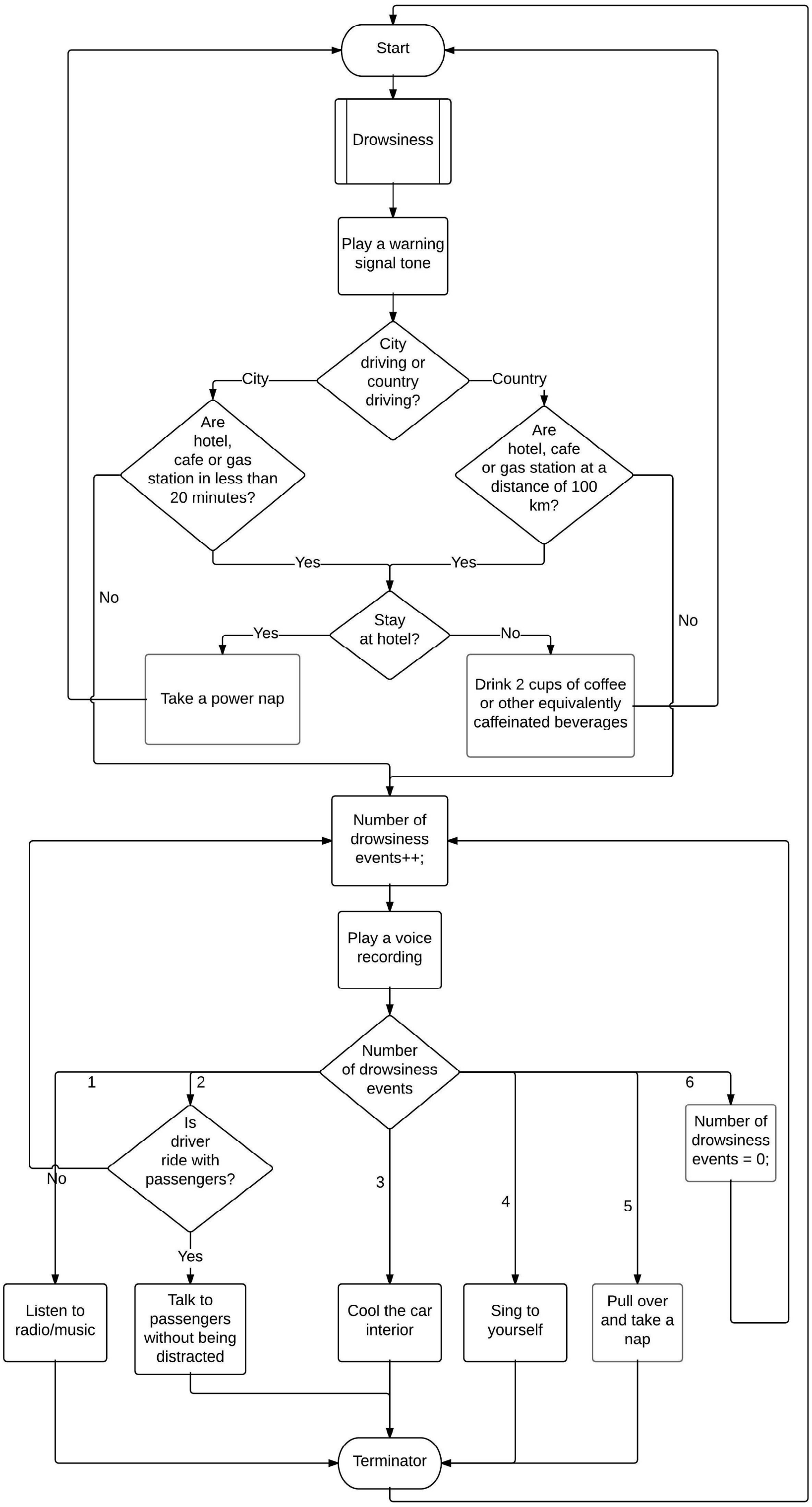

Fig 2. Flow chart of drowsiness state avoidance

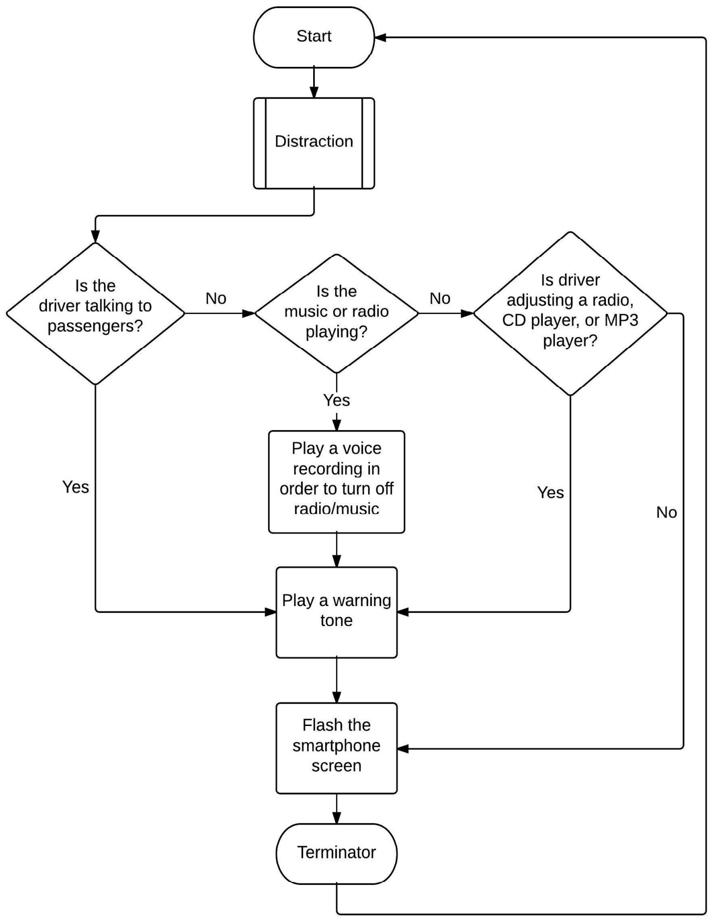

Fig. 3. Flow chart of distraction state avoidance

characteristic is present i.e. a face can be classified with regards to whether its eyes are open or closed. Both of these classifications rely upon landmark detection. A landmark is a point of interest within a face. The left eye, right eye, and nose base are all examples of landmarks. Classification is expressed as a certainty value, indicating the confidence that the facial characteristic is present. In our case, a value of 0.3 or less for the eye state classification indicates that it is likely that person's eyes are in a closed state.

As for code, we create and start a pipeline that continuously receives preview frames from a camera source for the front facing camera, runs detection on the frames, manages tracking of the most prominent face, and delivers continuous update notifications over time to a developer-defined "FaceTracker" instance.

To find face in the image the built-in "FaceDetector" class is used. We create a face detector, which is optimized for tracking a single, relatively large face. Additionally, a "LargestFaceFocusingProcessor" face processor is applied that focuses on tracking a single "prominent face", in conjunction with the associated FaceDetector. A prominent face is defined as a face, which was initially the largest, most central face when tracking began. This face will continue to be tracked as the prominent face for as long as it is visible, even when it is not the largest face. As an optimization, once the prominent face has been identified, the associated detector is instructed to track only that face. This makes face tracking faster.

We improved the overall speed and efficiency of our application by applying several optimization techniques. To improve the frame processing performance, we first set the width and height of the camera frames to 640 x 480 pixels. Also we adjusted the requested frame rate to 30 frames per second.

The Fig. 4 and Fig. 5 illustrate the UI of mobile application. 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 Euler Y and Euler Z angles characterize a face's orientation. The "Left eye OP" and "Right eye OP" parameters show the probabilities whether the left or right eye, respectively, is open. The higher value of these measurements is on the image, the higher probability that the eyes are open.

In the Fig. 4, a drowsiness state is detected. In this prototype, every time closed eyes are detected at a given point of time, timers will be activated to determine the duration of that state every 10 seconds. If the timer exceeds the duration of time considered to be safe to keep eyes closed while driving, the application will show drowsiness alert for a driver. As shown in the Fig, 4, the eyes are closed and this is confirmed by low probability values of left and right eye's openness equal to 0.03 and 0.02 respectively.

A similar algorithm corresponds to the distraction state that is recognized in the Fig. 5. Every time driver's face is not facing forward at a given point of time, timers will be activated to determine the duration of that state. If the timer exceeds interval of 2 seconds, application will show a distraction alert. The Fig. 7 shows that the head turn angle (Y) is greater than 15° and, thus, the distraction state is recognized.

The example of application for situation analysis, running on the smartphone Lenovo K910L that is mounted on the windshield of a car, is shown in the Fig. 6.

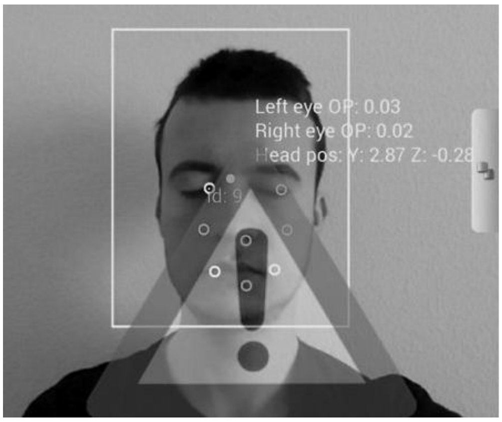

Fig. 4 An example UI screenshot of the application, which indicates drowsy driving state

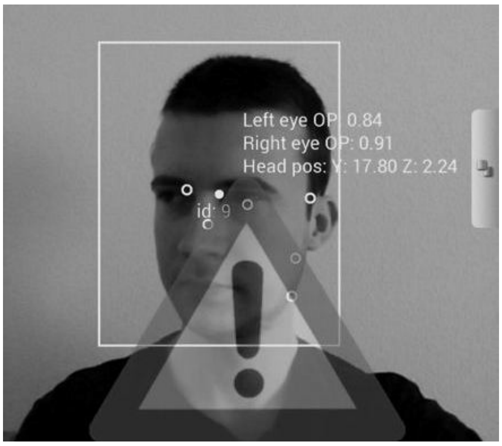

Fig. 5 An example UI screenshot of the application, which indicates distraction-driving state

V. CONCLUSIONS AND FUTURE WORK

The paper presented algorithms for determining of dangerous events and driver behaviour strategies as driver assistant in the vehicle. For identification of dangerous events based on information from smartphone cameras and vehicle sensors, a special diagram has been proposed.

In this paper, we focused on two dangerous events identification: drowsiness and distraction. The demo version of the mobile application for Android-based devices was presented. This mobile application is able to detect dangerous situations and make recommendations to the driver how to prevent road accidents. Our future work is to carry out research in order to verify other driving unsafe situations like as driver's irritability and in-car pipeline's tailgating and careless lane change.

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Fig. 6 The use of mobile application, running on the smartphone mounted on the windshield of a car

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