Decision Support System for Drivers & Passengers: Smartphone-Based Reference Model and Evaluation

Alexey Kashevnik
ITMO University
St.Petersburg, Russia
alexey@iias.spb.su

Igor Lashkov
ITMO University
SPIIRAS
St.Petersburg, Russia
igla@iias.spb.su

***Abstract*—Last years, decision support systems brought a lot of new possibilities for the people. Developing such technologies as context-aware recommendations, personification, cloud computing allows to support vehicle drivers and passengers in their trips. Decision support systems for vehicle drivers and passengers allows one to provide context-based personalized recommendations based on determined situation in the vehicle cabin and location region as well as driver preferences. For example, during the trip the driver can be notified about the interesting places. If the system determines the dangerous state it generates recommendations for the driver to predict the emergency situation. The paper presents a reference model of the decision support system, describe the dangerous state identification scheme, and discuss evaluation.**

I. Introduction

Decision support systems is the class of systems that is aimed at decision support of the person using the modern technologies such as context-aware recommendations, personification, and cloud computing [1]. For the vehicle drivers decision support systems open the new perspectives to make trips more comfortable and safe [2]. Along with that the tourism industry has become more and more popular last years. There are a lot of research and development implemented in this area (such as [3]).

Presented in the paper decision support system for vehicle drivers and passengers allows to provide them context-based personalized recommendations based on determined situation in the vehicle cabin, location region as well as driver preferences. The system determines the current driver dangerous state and based on this information generates recommendations. If the driver is in normal state the system can propose to attend some interesting places and provide information about them. In case of determined drowsiness or distraction dangerous state the system proposes recommendations aimed at returning the driver to normal state to predict the emergency situation.

The system uses the personal driver smartphone mounted in the vehicle windshield for tracking driver face and head as soon as get information from sensors (such as accelerometer, gyroscope, etc.). Based on this information the dangerous states (drowsiness and distraction) are determined using the proposed algorithms. The recommendations are generated for the driver based on determined dangerous states and current situation in the vehicle location. During the driving the driver and passenger get context based personified information about the interesting places around using.

The paper presents a reference model of the developed decision support systems, discuss the dangerous state identification and presents evaluation. The evaluation of the approach is based on the earlier developed Drive Safely system [4], [5]. The recommendation generation of interesting places is implemented based on developed by authors earlier Tourist Assistant – TAIS [6], [7].

The paper is structured as follows. Section II describes the related work in the area of vehicle driver support. The reference model of the developed system is presented in section III. Section IV presents the dangerous states identification scheme. Evaluation is described in Section V. Main results are summarized in the conclusion.

II. Related Work

Driver behavior is one of the main indicators signaling an unsafe situation that can help to early recognize drowsiness or distraction state and provide appropriate recommendations. For instance, the study [8] presents a drowsiness classification scheme based on the data from 30 drivers who repeatedly drove in a driving simulator (VTI Driving Simulator III [9]), both in alert and in sleep deprived conditions. Driver sleepiness is classified with the help of four separate classifiers: k-nearest neighbors, support vector machines, case-based reasoning and random forest, where physiological signals (power spectral density being a frequency of EEG signals, blink duration, PERCLOS being a percentage of eye closure) and contextual information (sleep/wake predictor based on the circadian rhythm, time awake, prior sleep and driving condition including road conditions) were used as sleepiness indicators. The sleepiness state of the driver is measured by rating scale KSS (Karolinska sleepiness scale). This study showed that driver sleep/wake contextual information is the most important feature of their entire dataset. According to the experiments of the study SVM performed well across all evaluations and was found to be the most stable classifier.

Another factor of driving behavior contributing high risk on driver performance is a distraction state. One of the popular distracted activities while driving is an instant messaging with smartphone among drivers of all ages. The paper [10] corresponds to the investigation of the texting with WhatsApp on driving performance. The results show a significant main effect of age for the driving-performance parameters. Texting

ISSN 2305-7254

WhatsApp messages while driving decreases driving performance for all age groups, most notably among older participants. In summary the negative effect of the use of the smartphone during driving is reflected in the number of collisions, with a greater risk of accidents in all the groups of drivers (by 8.3% for young adults, 25.0% for adults, 80.5% for middle-aged adults, and 134.5% for older drivers). The authors of this study recommend to include nonstandard vision tests, such as the measurement of the contrast sensitivity and the level of retinal stray light, in the visual examination for the driving license because these measurements have a significant impact on driving performance.

One of the possible approaches to evaluate distraction is based on the analysis of eye movements [11]. This study proposes a method for evaluating driver distraction based on the difference between simulated and observed eye movements, focused on the active use of vestibulo-ocular reflex (VOR) model and optokinetic reflex (OKR) model. According to the results of the experiments from driving simulator (CarSim, Mechanical Simulation Co., Ann Arbor, MI) the VOR+OKR model performs better than the VOR model with a smaller mean-square error, reduces the effect of optic flow, and works well with changing gaze in the case of involuntary eye movement. Thereby, this new combined model has a good potential to develop a driver detecting distraction system.

Driver safety awareness is extremely important in order to leverage the effectiveness of advanced driver assistance systems (ADAS) comprised of different technologies. Paper [12] is focused on exploring what kind of information users know about ADAS, how they acquired it and which methods they would referrer to learn about the system's limitations and capabilities. It presents the analysis of the in-depth interview including the answers from 38 Czech owners of cars with Forward Collision Warning (FCW) and Adaptive Cruise Control (ACC). The results of this interview show that the main reason for acquiring FCW or ACC is their presence in a bargain package or in the chosen vehicle. Moreover, ADAS limitations were something the drivers usually had to experience on their own without previous knowledge. According to the results, some car owners of ADAS systems often do not read the user's manual and they might not even know how to turn the systems on and off, and if they do, they often found out by trial-and-error experience. Besides, along the trip drivers face with problematic situations (e.g. the activity of the system above/under certain speed limits or in worsened weather conditions) and have to adjust their behavior and system use to. The results of the study show that the driver education concerning ADAS need to be more systematic and user-centered approach for learning driver safety methods and technologies should be provided.

III. Reference Model

The reference model presented in the paper (Fig. 1) of the dynamic traveler support system is aimed at driver and passenger support in the vehicle during the trip. The model is focused on the dangerous states identification with the information from the front-facing camera and sensors of smartphone as soon as context-based tour route generation and information representation. If the driver travels with passenger the tour and information about attractions are formed based on passenger preferences. If the driver travels alone his/her preferences are used for tour route generation and information representation. In this case, the driver gets information about attraction interesting for him/her only when the vehicle is stopped (red traffic light, traffic jam, parking position and etc.).

Two dangerous states, i.e. drowsiness and distraction, are detected by the image processing algorithms. Information from the front-facing camera and sensors of the smartphone is used for the dangerous states determination. Head movements, facial expressions, and the prolonged and frequent eye blinks are monitored to determine drowsiness state. The following visual cues are relevant to the drowsiness state: percentage of closure of eyelid (PERCLOS), eye blink time, eye-blinking rate, eye gaze, pupil movement, and eyelid movement. To identify the distraction dangerous state the system tracks whether the driver looks forward to the road. For this purposes the angle between the road and driver face direction is determined.

Tour route generation and information representation (guiding, narration, presentation of additional information) is based on the personal schedule analysis, current situation monitoring and prediction, and integration of the on-board infotainment system with personal smartphone and external services. Vehicle infotainment system provides vehicle context (speed, acceleration, location, information from telemetry) as soon as provides possibilities to use speakers and/or display for presenting information to the passenger or the driver during stops. Information representation is implemented earlier based on the personalized tourist assistance service (TAIS) [20]. The tour is generated based on the preferences stored in the tourist's profile, situation in the region and its possible development (e.g., regular traffic jams during rush hours can be easily predicted), and available information about attractions. Passenger(s) can use their smartphones during the tour for narration, imagery and video synchronized with the vehicle's location, speed and orientation. Guiding information is obtained from the accessible smart city services and predefined libraries.

Intelligent support system interacts with the cloud to enhance the quality of the information provided to the driver or/and passenger. The cloud keeps such information as driver / passenger preferences, his/her personal schedule. At the same time the following information characterizes the driver while controlling the vehicle: vehicle control statistics, driver groups, and trip reports. Vehicle control statistics keeps information about vehicle movements and driver actions in the cabin as well as information about dangerous states determined by the system. Driver groups are used in driver classification by their behavior that is used by the system for group recommendation generation. Trip reports contain summary information about driver trips that is useful for further human analysis. Environment context service provides to the cloud information about current situation in the region: season, weather, traffic jams and etc. Computation service provides computation resource that are used for offline resource-intensive calculations. Attraction information aggregation service is aimed at information extraction from different internet services and keep it in the attraction database.

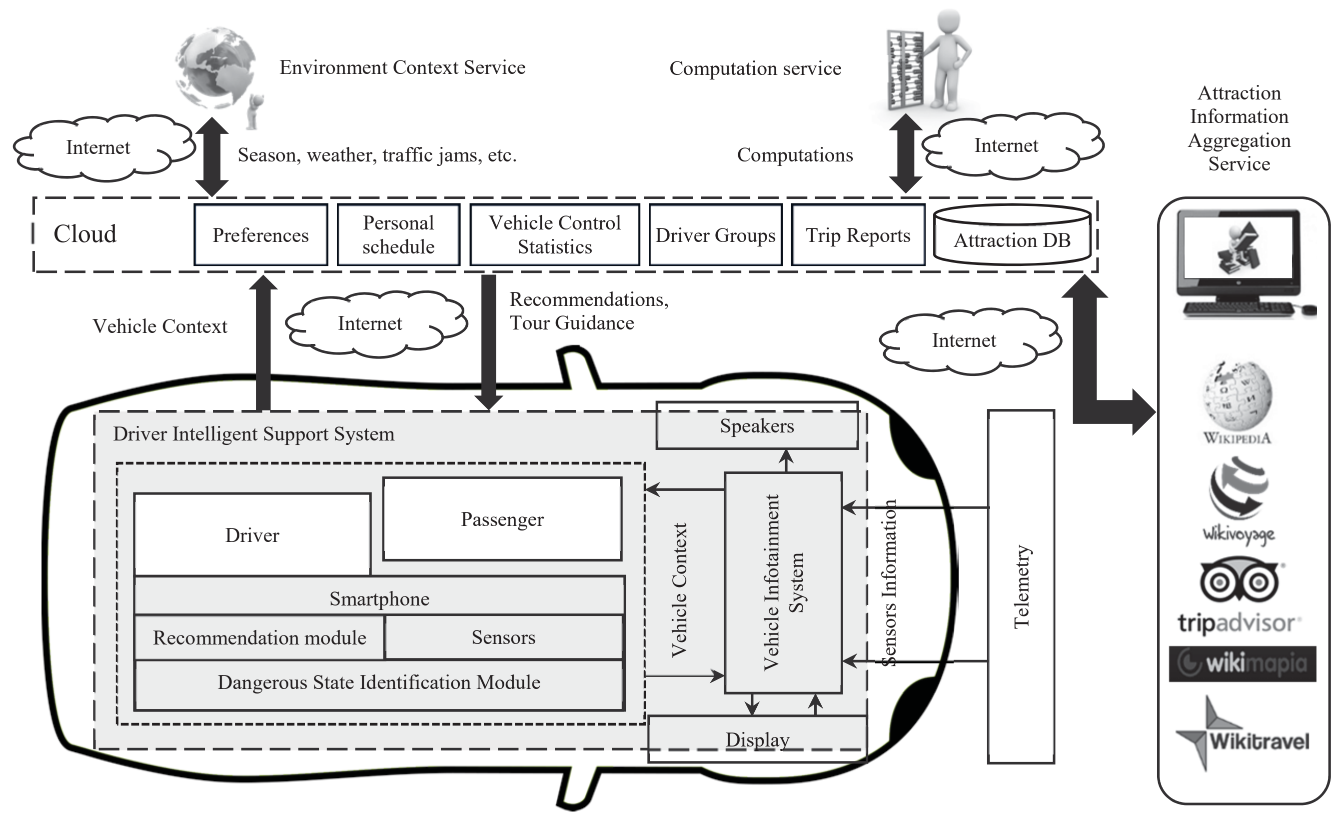

Fig. 1. Reference model of the decision support system for vehicle drivers

IV. DANGEROUS STATES IDENTIFICATION

Dangerous State Identification Module is focused on the identification of the drowsiness or distraction dangerous states using the information from smartphone camera and sensors.

Dangerous driving state t_s, can be presented in a form of time series (Fig. 2) 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}.

Based on the publication analysis on driver behavior and traffic safety, the time-to-collision (TTC) parameter has been proposed to be a reliable measure for monitoring dangerous situations in active safety systems, defined on the interval of *[2; 3]* seconds. TTC depends not only on the current driving conditions, but also on the driver reaction time (RT). TTC includes the time of dangerous situation identification up to the time of decision-making and the time required to recognize the driver dangerous state t_s, comprising n number of dangerous situations t_e, indicating its state. It is worth noting that RT is limited by the interval of *[0,5; 1,5]* seconds, specified individually for a driver.

One of the key input parameters, undefined previously, is an overall number of dangerous situations (minimum) in time interval, denoting one or another dangerous state t_s, equal to TTC, except the driver's reaction time. This parameter depends on the time of processing dangerous situations t_e and the driver's reaction time $t_{reaction}$ [13]. According to the studies in the field of exploring RT and TTC 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:

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

where $n \in [1,\ 101]$ is a dimensionless quantity, equal to the number of measured dangerous situations, $E \in [1,\ 5]$ is factor of smartphone computing power, $t_{reaction} \in [0.5,\ 1.5]$ sec. 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, and vice versa 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.

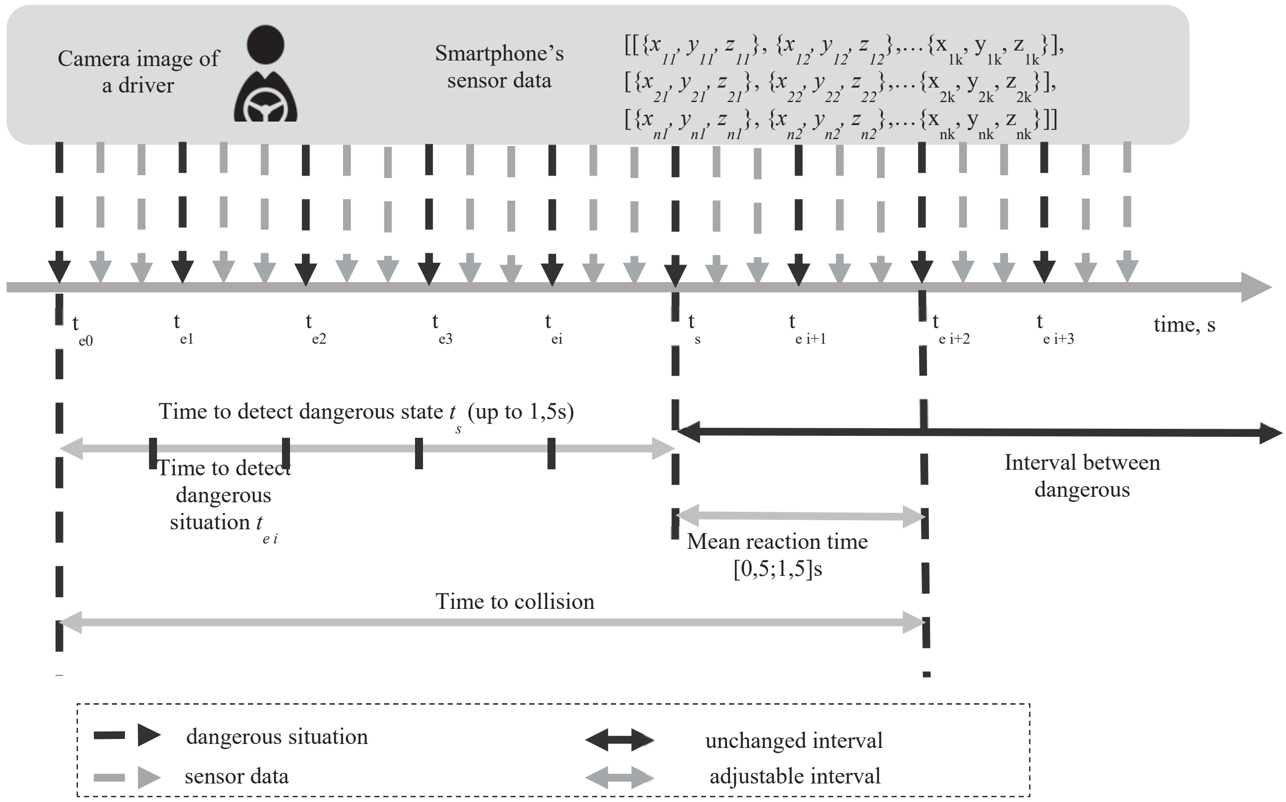

Fig. 2. Dangerous states identification scheme

It is worth noting that the mean reaction time for a driver to react to a dangerous state depends not only on the individual characteristics of the driver, gender [14], age [14], but also on his current travel time, vehicle speed 0. According to the parameters above, the mean RT is proposed to be detected as follows:

$$t_{reaction} = \frac{A\times\omega_1 + G\times\omega_2 + DT\times\omega_3}{V\times\omega_0}, \quad (1)$$

where $t_{reaction}$ is the driver's reaction time, $A \in [18, 100]$ is the driver's age, G is the driver's gender, DT is a travel time (minutes), V is a vehicle speed (km/h), $\omega_0, \omega_1, \omega_2, \omega_3$ are the coefficients (weights) for each of the listed parameters, respectively. V is the only inverse proportional parameter to all others in a formula for detecting driver's reaction in which the increase (decrease) of this parameter leads to decrease (increase) of the driver's response time to react on dangerous situation and vice versa.

V. Evaluation

The relationship of the number of dangerous situations on the driver's reaction time and the factor of smartphone computing power is clearly shown in Fig. 3. According the earlier conducted experiments the number of frames unveiling the dangerous situations is defined as five being quite reliable for detecting driver dangerous state. It is worth noting that this number can be increased or decreased depending on the driver's reaction time and smartphone computing power in order to process dangerous events beforehand and alert driver to take action and prevent a traffic accident. On the one hand, faster driver's response (lower reaction time) to the road situation makes system possible to leave more time to detect dangerous situations for the allotted time of 2 seconds, but on the other hand, slower response (higher reaction time) restricts system efficiency in a way to detect dangerous state in a driving behavior accurately. One more parameter, that affects system performance and productivity when monitoring driving behavior, is a smartphone computing power, characterizing the ability of the smartphone to leverage the time-consuming offline operations. The tested smartphone models of 3-3,5 years in mid-price segment and flagship models are reasonably fast enough to process up to five dangerous states under the condition that the reaction time is less than 1.2 seconds that is suitable in most situations (see Fig. 4). In situation that the driver's reaction time is rather high (slow response) and smartphone computing power is limited and is nearly at the lower bottom of the provided range, the number of being processed frames of the driver's face n by the image of the smartphone's front-facing camera significantly decreases that leads to inaccurate work of the proposed driver safety system.

Comparison of the time recognition to detect dangerous state in driving behavior with smartphones of different models and manufactures used in the experiments is presented in Fig. 4.

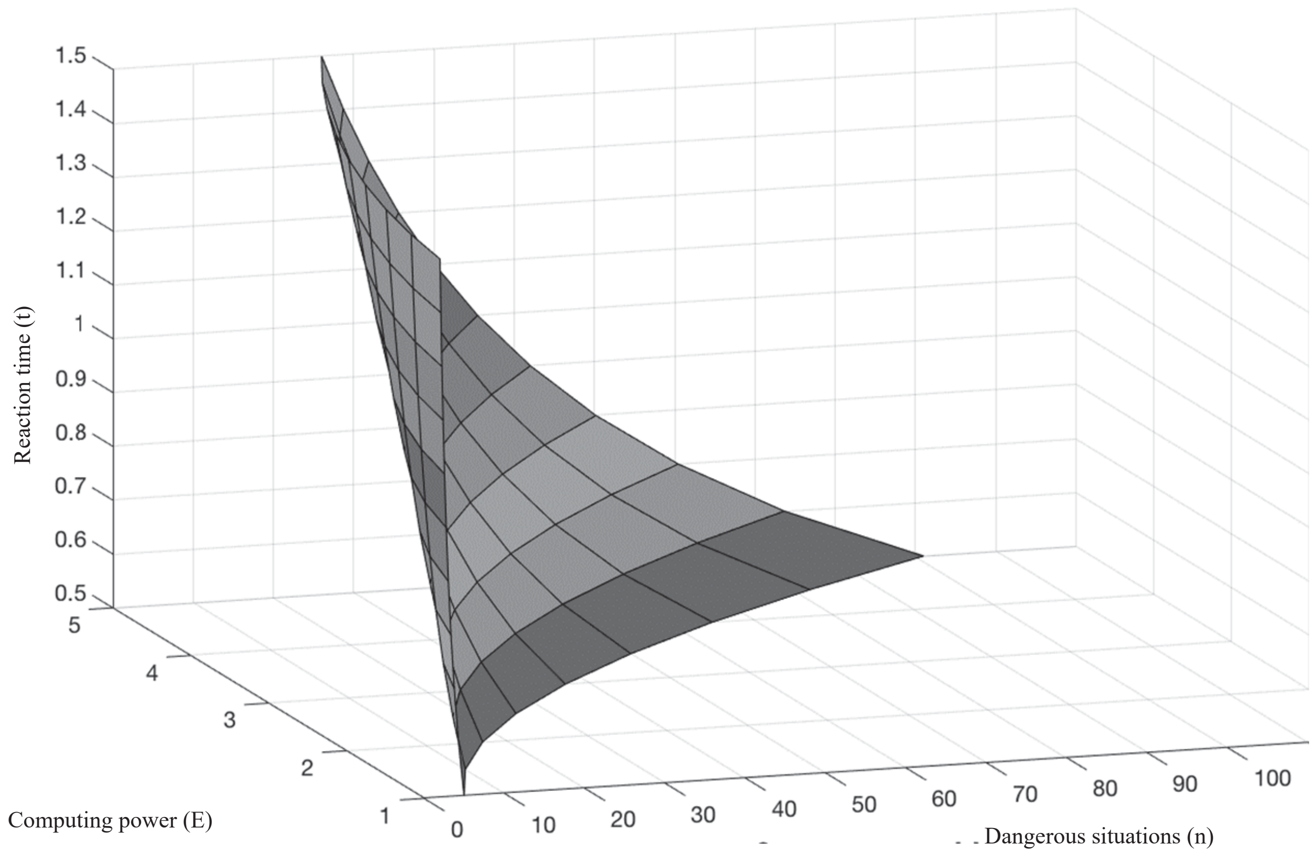

Fig. 3. Relationship of the number of dangerous situations on the driver's reaction time and smartphone computing power

E is a smartphone computing power, n is the number of frames by the image of driver's face being processed, t denotes the time that the smartphone utilizes to recognize dangerous state in driving behavior. Evaluation of the time required to recognize dangerous state of the driver was conducted provided that the driver's reaction time is defined as a constant value equal to one second, being a quite common for drivers in average. The most of the presented smartphones that are mid-range phone or flagships may recognize more than five dangerous situations in two seconds that is a high bound of the acceptable range. In this case the proposed driver safety system works with high accuracy and recall that increases the driver safety. Other part of the smartphones that are low-budget devices may operate with some losses in accuracy and performance of dangerous state detection in driving behavior that can affect the safety system overall performance.

VI. Conclusion

The paper presents the reference model of the decision support system for vehicle drivers and passengers based on information from smartphone camera and sensors. The model is based on the cloud computing, context based recommendation, and personification technologies. The cloud computing technology allows one to accumulate the statistics of the system usage and use it for the further analysis. Context-based recommendation technology allows to generate recommendations for the driver and passenger based on current situation in the vehicle and in the location region. Personification technology allows taking into account driver and passenger preferences for the recommendation generation. Current situation in the vehicle cabin is determined by dangerous states identification scheme that is designed to determine distraction or drowsiness dangerous states during the driving.

Evaluation shows that the presented reference model and scheme are applicable for the modern smartphones and their computation power is enough to implement the tasks designed in the reference model and dangerous states identification scheme. Showed graph of the relationship between the number of dangerous situations on the driver's reaction time and smartphone computing power has been calculated to show the system performance based on the different smartphones. Tests shows that most popular smartphones (price started from 150 USD) have enough computation resources to work with the proposed system.

Acknowledgment

The research is funded by the Russian Science Foundation (project # 18-71-10065).

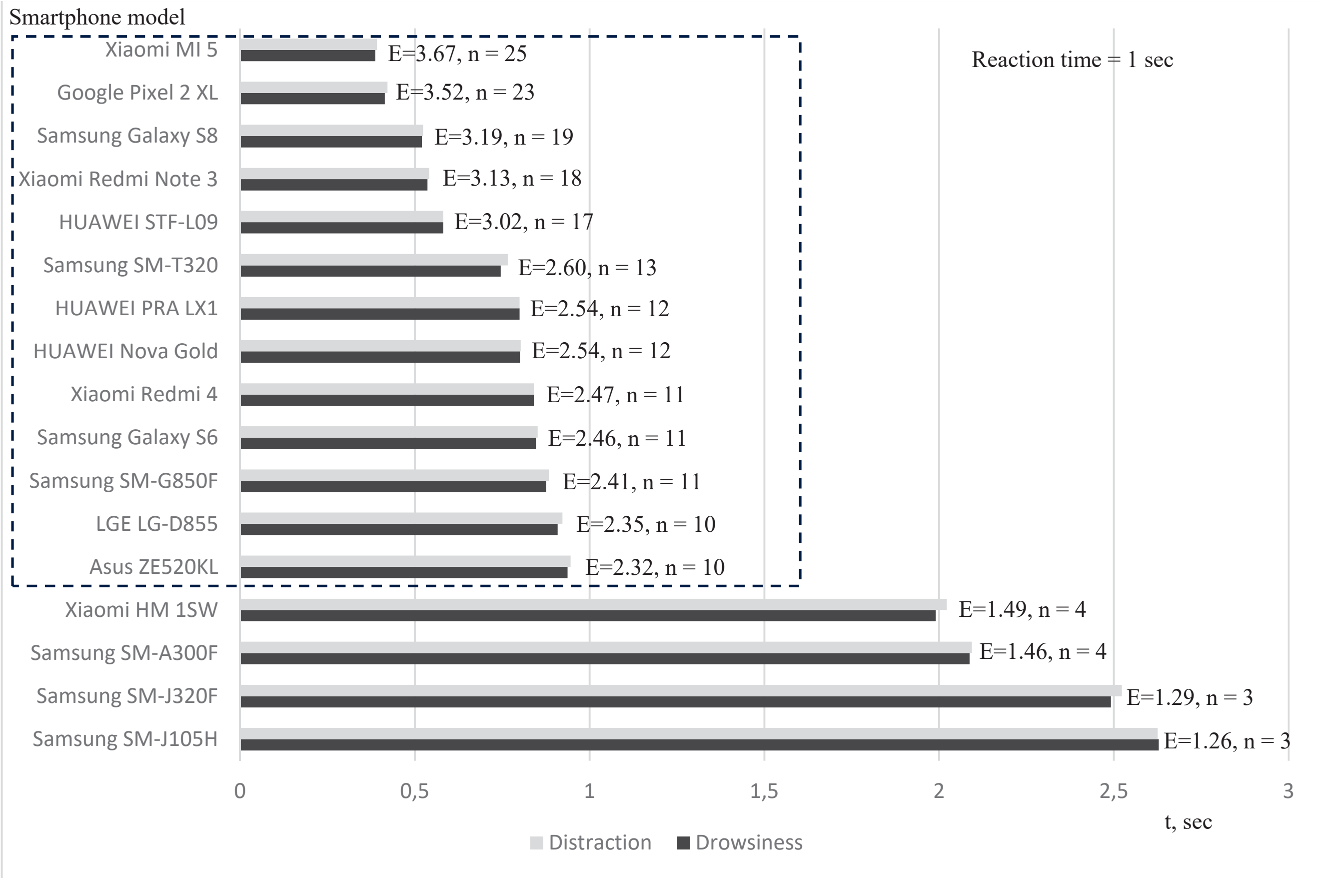

Fig. 4. Evaluation of time recognition to detect drowsiness and distraction by vehicle safety system

REFERENCES

[1] A. Smirnov, A. Ponomarev, N. Shilov, A. Kashevnik, N. Teslya, "Ontology-Based Human-Computer Cloud for Decision Support: Architecture and Applications in Tourism", *International Journal of Embedded and Real-Time Communication Systems (IJERTCS)*, vol.9(1), 2018, pp. 1-19.

[2] B. Ryder, B. Gahr, P. Egolf, A. Dahlinger, F. Wortmann, Preventing traffic accidents with in-vehicle decision support systems - The impact of accident hotspot warnings on driver behaviour. *Decision Support Systems*, vol.99, 2017, pp. 64–74.

[3] S. Marchenkov, A. Vdovenko, D. Korzun, "Enhancing the Opportunities of Collaborative Work in an Intelligent Room using e-Tourism Services", SPIIRAS Proceedings, vol.1(50), 2017, pp. 165-189.

[4] A. Smirnov, A. Kashevnik, I. Lashkov, V. Parfenov, "Smartphone-Based Identification Of Dangerous Driving Situations: Algorithms and Implementation", *Proceedings of the 18th Conference of Open Innovations Association FRUCT*, St.Petersburg, Russia, 18-22 April 2016, pp. 306-313.

[5] A. Kashevnik, I. Lashkov, V. Parfenov, N. Mustafin, O. Baraniuc, "Context-Based Driver Support System Development: Methodology and Case Study", *Proceedings of the 21st Conference of Open Innovations Association FRUCT*, Helsinki, Finland, Nov. 2017, pp. 162-171.

[6] A. Smirnov, A. Kashevnik, A. Ponomarev, N. Shilov, N. Teslya, Proactive Recommendation System for m-Tourism Application. B. Johansson, B. Andersson, N. Holmberg (eds.) Perspectives in Business Informatics Research, Proceedings of the 13th International Conference on Business Informatics Research (BIR 2014), Springer, LNBIP 194, 2014, pp. 113-127.

[7] A. Smirnov, A. Kashevnik, A. Ponomarev, "Context-based infomobility system for cultural heritage recommendation: Tourist Assistant—TAIS", *Personal and Ubiquitous Computing*, vol.21(2), pp.297-311.

[8] S. Barua, M. Uddin Ahmeda, C. Ahlström, S. Begum, "Automatic driver sleepiness detection using EEG, EOG and contextual information", *Expert Systems with Applications*, 2019, pp. 121-135.

[9] VTIS Driving Simulator, https://www.vti.se/en/research-areas/vtis-driving-simulators/

[10] C. Ortiz, S. Ortiz-Peregrina, J. Castro, M. Casares-López, C. Salas, "Driver distraction by smartphone use (WhatsApp) in different age groups", *Accident Analysis & Prevention*, 2018, pp. 239-249.

[11] A. Le, M. Inagami, H. Hamada, T. Suzuki, H. Aoki, "Towards online detection of driver distraction: Eye-movement simulation based on a combination of vestibulo-ocular reflex and optokinetic reflex models", *Transportation Research Part F: Traffic Psychology and Behaviour*, 2018, pp. 1-14.

[12] L. Viktorová, M. Šucha, "Learning about advanced driver assistance systems – The case of ACC and FCW in a sample of Czech drivers", *Transportation Research Part F: Traffic Psychology and Behaviour*, 2008, pp. 1-8.

[13] M. Green, "How Long Does It Take to Stop? Methodological Analysis of Driver Perception-Brake Times", *Transportation Human Factors*, vol.2(2), 2000, pp. 195-216.

[14] L. Warshawsky-Livne, D. Shinar, "Effects of uncertainty, transmission type, driver age and gender on brake reaction and movement time" *Journal of Safety Research*, vol.33(1), 2002, pp. 117-128.

J. Törnros, "Effect of driving speed on reaction time during motorway driving", *Accident Analysis and Prevention*, vol.27(4), 1995, pp. 435-442.