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# CONTEXT-BASED RIDER ASSISTANT SYSTEM FOR TWO WHEELED SELF-BALANCING VEHICLES

*Kim J., Sato K., Hashimoto N., Kashevnik A., Tomita K., Miyakoshi S., Takinami Y., Matsumoto O., Boyali A.* **Context-Based Rider Assistant System for Two Wheeled Self-Balancing Vehicles.**

**Abstract.** Personal mobility devises become more and more popular last years. Gyroscooters, two wheeled self-balancing vehicles, wheelchair, bikes, and scooters help people to solve the first and last mile problems in big cities. To help people with navigation and to increase their safety the intelligent rider assistant systems can be utilized that are used the rider personal smartphone to form the context and provide the rider with the recommendations. We understand the context as any information that characterize current situation. So, the context represents the model of current situation. We assume that rider mounts personal smartphone that allows it to track the rider face using the front-facing camera. Modern smartphones allow to track current situation using such sensors as: GPS / GLONASS, accelerometer, gyroscope, magnetometer, microphone, and video cameras. The proposed rider assistant system uses these sensors to capture the context information about the rider and the vehicle and generates context-oriented recommendations. The proposed system is aimed at dangerous situation detection for the rider, we are considering two dangerous situations: drowsiness and distraction. Using the computer vision methods, we determine parameters of the rider face (eyes, nose, mouth, head pith and rotation angles) and based on analysis of this parameters detect the dangerous situations. The paper presents a comprehensive related work analysis in the topic of intelligent driver assistant systems and recommendation generation, an approach to dangerous situation detection and recommendation generation is proposed, and evaluation of the distraction dangerous state determination for personal mobility device riders.

**Keywords:** Context, Rider Assistant, Vehicle, Drowsiness, Distraction.

**1. Introduction.** Dangerous situation detection and accident prevention is a popular research direction in recent years [1-3]. Distraction is a dangerous state that can cause traffic accidents, vehicle damage, inference to other riders / drivers, non-eco-friendly driving, and etc. Timely distraction detection allows to prevent these negative aspects. Distracted riding is any activity that diverts attention from driving, including talking or texting on smartphone, eating, drinking, talking with other people, fiddling with the vehicle infotainment or navigation system [4]. That is, it indicates that the rider does not concentrate on the operation of the vehicle or concentrate on other activities.

In scope of the paper we consider the riding of personal mobility devices (PMD) that are sensitive to the rider distraction. Research in the area of PMD have been actively conducted last years as these devices are promising alternatives in solving the first and last mile for people transportation. The PMDs can be classified into standing type PMDs, two-seater ultra-small devices and electric bicycles. Among them, the standing type PMDs have gained a great deal reputation due to their unique motion capabilities.

We present the context-based rider assistant system that is aimed at drowsiness state determination based on information from smartphone camera and sensors in real time. We assume that the PMD has possibility to fix the smartphone in the following way. The front-facing camera should capture the rider's face and angle between front rider view and the smartphone is minimal (as soon as possible) but therefore the smartphone should not obstruct the road view for the rider. The rider assistant system is described in details by authors in the following papers [5-10]. This paper is aimed at description of the applicability of the system for PMD riders and experiments that have been conducted to study the dependency of the rider distraction to the PMD trajectory. For distraction modelling authors propose participants to gaze in specified point as well as making phone calls and messaging.

The paper is structured as follows. Section 2 presents a related work analysis in the topic of intelligent rider assistant systems and recommendation generation. Section 3 describes the developed rider assistant system. Section 3 shows the conducted experiments. Conclusion summarize the paper.

**2**. **Related Work.** The way the vehicle safety systems operate they can be divided into the following groups: advanced driver assistance systems, presenting a hardware-software complex, installed by automotive manufactures at the production; mobile recommendation systems developed as the software solutions in a form of mobile applications [11]; camera surveillance systems installed in a vehicle cabin and used for continuous monitoring of a driver or a road; wearable electronics used by a driver as the body-worn accessories.

The main goal of the existing smartphone-based research studies and solutions is to early warn driver about recognized dangerous state and eliminate the risk of drowsy or distracted driving. Let's consider driver's drowsiness determination related studies. This study [12] demonstrates a monitoring system developed to detect and alert the vehicle driver about the presence of the drowsiness state. To recognize whether the driver is drowsy, the visual indicators that reflect the driver's condition, comprising the state of the eyes, the head pose and the yawning, were assessed. The number of tests were proposed to assess the driver's state, including yawning, front nodding, blink detection, etc. Although the proposed recognition method gets 93% of total drowsiness detections, its unclear which dataset was utilized to evaluate the system and whether the detection method was tested under different light conditions. In this study the Android-based smartphone was utilized to assess the driver's state.

The study [13] demonstrates that detection of blinks can be affected by the driver state, level of automation, the measurement frequency, and the algorithms used. It proposes the evaluation of the performance of an electrooculogram- and camera-based blink detection algorithms in both manually and conditionally automated driving conditions under various constraints. During the experiment, the participants were requested to rate their subjective drowsiness level with the Karolinska Sleepiness Scale every 15 minutes.

Another study [14] presents the developed smartphone mobile application "Drowsy Driver Scleral-Area" related to driver's drowsiness detection. The proposed mobile application includes a Haar cascade classifier, provided by the computer vision framework OpenCV [15] for driver's face and eyes detection; and a module written in Java and responsible for image processing and alerting driver about potential hazards while driving. The developed application is configured to detect prolonged eyelid closure exceeding three seconds indicating drowsiness state. Also, it was tested on a static photo sequence, person in a laboratory and in a vehicle. The paper highlights that the pixel density analysis method was used that eliminates the need to manually count pixels and determine a threshold for drowsiness. It involves the calculation of the ratio of white pixels to maximum white pixels (corresponding to full eye opening) in the region of detection. The authors of the study consider that additional tests need to be conducted under more dynamic motion and reduced light conditions.

One more paper proposes the three-stage drowsiness detection framework for vehicle drivers, developed for Android-based smartphones [16]. The first stage uses the PERCLOS obtained through images captured by the front-facing camera with an eye state classification method. The system uses near infrared lighting for illuminating the face of the driver while night-driving. The next step uses the voiced to the unvoiced ratio calculated based on the speech data taken from the built-in smartphone microphone, in the event PERCLOS crosses the threshold. A final stage is used as a touch response within a specified time to declare the driver as drowsy and subsequently alert with an audible alarm. According to the received results of the study the developed framework for smartphones demonstrates 93% drowsiness state classification. The final measurement indicators used in this study include PERCLOS, the voiced-unvoiced ratio and a reaction test response of the driver on the smartphone screen.

Other more sophisticated approach includes the detection of sleep deprivation by evaluating a short video sequence of a driver [17]. It utilizes the OpenCV Haar Caascades to extract the driver's face from every frame and classify it within the deep learning framework into two classes: "sleep derived" and "rested". In detail, this approach is based on the use of the trained model formed by the non-linear models MobileNets, adapted specifically for mobile applications on smartphones. The output of MobileNet for camera frame is the estimation of the probability of the frame to belong to “sleep deprived” class. In case the probability of this class is more than 0.5, the driver in the frame is classified as “sleep deprived”. The real experiments have been conducted with aid of prototype implemented as an Android-based mobile application for smartphone. TensorFlow lite framework was utilized to compile the MobileNet model previously trained on a standalone laptop.

Another major cause for road accidents is driver’s distraction. This paper proposes a smartphone camera-based driver fatigue and distraction monitoring system while driving [18]. This study heavily relies on monitoring driver’s eyes and mouth, and detecting eye rub due to irritation in eye and yawning through intensity sum of facial region. The evaluation of the proposed approach is done using the developed mobile application for Android platform with Xiaomi Redmi 1s smartphone. The authors of the study conducted the experiments and only evaluated the CPU load and the battery consumption of the developed system. They concluded their system consumed 12% of battery of continuous use for a one hour. The paper highlights that the proposed approach is not suitable for work under low/no light conditions.

Another study [19] is focused on developing Driver Fatigue Detection System aimed at monitoring driver behavior and alerting him to prevent from falling asleep while driving. The proposed solution is adapted for working on the smartphone, utilizing built-in camera for recording video and processing it for real-time eye-tracking. The authors of the study admit that their solution is limited due to external illumination conditions and wearing sunglass by a driver.

Other paper [20] evaluates the pertinence of using driver head rotation movements to automatically predict the smartphone usage while driving. The duration a driver spends looking down from a reference neutral direction is used as a parameter to predict the smartphone usage. According to the conducted experiments, a smartphone usage detection system based on real-time video analysis of head movements is implemented in this study. It performs the real-time video analysis of the driver’s face, evaluates its head rotation deviation from neutral orientation when the driver is looking at the road, and detects whether the percentage of these deviations exceeds a threshold.

To monitor the driver’s vigilance level and recognize its fatigue state, the study relies on multiple visual indicators, including eye blinking, head nod and yawning [21]. Real-time detection is based on the use of the face and eye blink detection with Haar-like technique and mouth detection for yawning state with canny active contour finding method. The proposed approach was implemented using Java programming language and OpenCV framework responsible for image processing that is supported by Android platform. According to the conducted experiments, the performance of the proposed method for face and eye tracking was tested under variable light conditions.

In the paper [22], a strategy and system to detect driving fatigue based on machine vision and machine learning AdaBoost algorithm is proposed. The entire detection strategy consists of the following operations: detection of the face using classifiers of the front and deflected face; extraction of eye region according to geometric distribution of facial organs; and, finally, trained classifiers for open and closes eyes are used to detect eyes in the selected regions. As a result, the PERCLOS measure is calculated and used as a measure for fatigue rate as well as the duration time of eye-closed state. Underneath, the OpenCV library was utilized to analyze frames for face recognition. In case the driver's fatigue state is recognized, the system will make an audible alert for a driver or dial the emergency center or police. The performance of the proposed system may decrease up to 10 frames per second. The developed Driving Fatigue Detection System is compatible with Android smartphones. It should be highlighted that the study misses the experiments in conditions under poor illumination.

Introduction of the emergency prevention system at some transport enterprise can improve the overall efficiency of using vehicles and reduce the operating costs of the whole enterprise. According to the considered papers and research projects [23] related to active safety systems all apparatuses and software methods applicable to building such kind of systems can be divided into two separate groups: the ones directed to monitoring in-cabin driving behavior and the other focused on tracking the road situation around the vehicle. As the driver monitoring in-cabin driving behavior is not sufficiently elaborated the main focus of the paper is based on the analysis of interaction between a driver and a vehicle.

Among the technical devices, specially designed and used at driving in order to recognize the signs of driver's distraction of drowsiness are wearable devices (e.g., cap, wristband) [24], measuring driver's health parameters with physiological indicators, including heartbeat, breathing rate, electroencephalography [25], electrodermal activity [26], etc.; video cameras keep an eye on a driver and employ recognition of facial features, such as turn and tilt of the head, frequency of eye-lids blinking, the eyes closure, etc.

Video cameras fixed inside the vehicle cabin and providing for continuous monitoring of the driver's behavior, are commonly used by active safety systems. These cameras are utilized for capturing a sequence of image frames at the predefined reading rate (e.g., 20 frames per second), the above is further used in image processing algorithms and then at instant recognition of certain objects on the image (head pose, facial features) and their parameters (determine size and color of the object, distance to it and the depth estimation). Using specialized software interfaces and methods the front-facing cameras built in smartphones provide a continuous series of images that can be utilized in digital image processing and driver's face recognition. Let us consider a number of approaches to facial recognition, comparing their advantages and disadvantages when applied in practice.

Currently the face detection technology [27] extensively applied in vehicle active safety systems is one of the trending technologies and developing areas of computer vision. The use of video cameras in construction of safety systems involves certain utilization methods of computer image processing in order to recognize the presence of the object, find its position in the coordinate systems of the original image. Depending on the algorithm selected for recognition the position of the object can be defined by the coordinates of rectangle, by the outline of this object or by a set of points describing it. It is worth mentioning that algorithms for finding objects on images primarily have to show maximum efficiency and performance in finding people's faces and their facial features. Methods for face recognition in images can be divided into two groups: methods based on the use of defined set of rules (template matching such as Viola-Jones algorithm [28]) and methods using vector of features for further image classification (appearance models, such as Hidden Markov models (HMM) [29], neural networks, linear discriminant analysis, etc.). Let us consider a number of methods in each mentioned category.

Viola-Jones algorithm originally adapted for real-time determination of faces in the images is a widely used method for finding objects on an image.

This algorithm uses the scanning window technique for finding people's face and facial features. Among the existing methods of object detection in images the Viola-Jones method shows one of the best results in terms of recognition efficiency and operation speed as well as a low false positive rate of face detection. The fact that this method imposes certain constraints on the spatial position of the face and its brightness level could be attributed as one of its disadvantages. The algorithm operates best and recognizes people's facial features at a slight angle (not exceeding 30 degrees). At the pitch angle of over 30 degrees the recognition rate is greatly reduced and it is impossible to recognize a person's face at an arbitrary angle of rotation.

The other common object detection method is based on the use of neural networks [30]. A distinctive feature of neural networks is the learning ability that allows for tackling tasks with high efficiency. The neural network is trained for a certain collection of input pattern pairs, whereas key features are extracted, and the relations are formed between them. Hereinafter, the trained neural network allows to recognize a previously unknown object by applying the experience gained during the training process. A convolutional neural network shows best results in recognition, however, it is considered the most difficult to implement. Network features such as total weights (face detection anywhere in the image) local receptive fields provide resistance to various distortions (offset, zoom, etc.). One of the advantages of using this method is the possibility of processing facial patterns at different pitch angles relatively to the vertical axis. At the same time the method has a number of disadvantages; one of them is the false detection of objects that vaguely resemble a person's face.

The face detection in the image can be provided by other adaptive method using Support Vector Machine (SVM) [31]. The SVM method considers each image as a point in n-dimensional space, where n corresponds to the data dimensions or the total number of pixels in the image. Each of these points belongs to a certain class. The main purpose of SVM is to find a plane, whereas the distance from the nearest point is maximal within the set of options, and the corresponding optimal classifier. In comparison with a trained neural network, that requires small computing resource; the operating time of SVM method could greatly increase if the number of vectors significantly exceeded the sample size. The advantages of this method include the relatively short training time and high accuracy of facial recognition in images.

The main difficulties encountered in the recognition of faces in images are the spatial characteristics, including face position and its scale, the number of faces in the image, the image resolution, possible artificial interference on the face (e.g., glasses, makeup, mask), light conditions, shades and reflections from surrounding objects. Algorithms for determining facial characteristics of the driver are actively used in existing active safety systems. It should be noted that the use of such algorithms in combination with other methods of recognition the dangerous driving behavior can improve the accuracy of dangerous state determination and the overall efficiency of the system.

Another approach to recognition of risky driving implies reading, storing and analyzing sensors' data gathered from built-in vehicle sensors, including radars, LIDARs and lasers. So, the main research and technological solutions are focused on the utilization of different machine learning algorithms and approaches to working with accumulated driving statistics in order to analyze the drivers' behavior patterns and estimate their driving style. Examples of the developed solutions are the telemetry systems, integrated in the vehicle at the stage of their production, as well as mobile applications, involving a number of built-in smartphone sensors.

Approaches based on the classification of drivers and the estimation of their driving style (typically described by aggressive, normal and calm values) utilize a wide range of algorithms, including dynamic time warping [32] for calculation of similarities between temporal sequences; fuzzy logic [33], based on a set of rules; clustering methods [34], grouping drivers with similar driving skills and experience; SVM; HMM and others. It should be noted, that the accumulated driving statistics allows for anticipating some sort of traffic situation and driver's early warning about possible emergency situation.

Upon the detection of possible emergency situation the active safety systems employ a number of technical methods to alert and warn driver to take actions to avoid the emergency. As an example, the driver fatigue monitoring system is one of the vehicle safety technologies that uses computer processing and image analysis methods in its work. Based on the analyzing of the steering wheel movement and the steering wheel angle, the system is able to recognize the driver's drowsiness and distraction and make a signal warning of the need to take a break in driving.

According to the level and force of perception, driver assistance methods applied inside the vehicle cabin can be divided into three categories: informational (e.g., audible warning signal), auxiliary (e.g., changing the force of pushing the accelerator pedal), and partial or complete intervention in control of the vehicle active safety system (e.g., reduce the fuel injection at exceeding a certain speed). The use of various measures to warn and prevent the occurrence of emergency situation helps to avoid a traffic accident.

As a rule, the active safety systems focused on early detection and warning the driver about possible traffic accidents, are gaining popularity and prevail on demand from a large number of automakers; the information about this type of systems is open in varying degrees and fragmented among the developers of these systems. Thus, in order to integrate and formalize data collected from active safety systems and ensure the implementation of the system use scenarios, it is proposed to develop an ontology model. One of the main advantages of ontologies using [35-37] is a systematic approach to the subject area description where concepts and relations are assigned unique names and definitions.

**2. Rider Assistant System.** For utilization of the proposed rider assistant system a rider has to fix his/her personal smartphone in the PMD. The smartphone monitors his/her face using the front camera during the riding of the PMD. Together with information from smartphone sensors the system can detect distraction dangerous situation for the rider.

For analysis of the rider head and face an approach has been proposed (see Figure 1). Every time when the mobile application gets image from the front camera this image is recognized and situation is estimated (is it dangerous or not). Then the process is repeated until the rider closes the application or stops dangerous situation estimation function.

The following three main components are presented in Figure 1 rider, smartphone, and cloud. Smartphone analyses the rider head and face and determine dangerous situations. Information for analyzing the rider head and face is collected by the mobile application component from the front camera using the image recognition. The application analyzes head movements (head rotation and nods), percentage of closure of eyelid (PERCLOS), eye blink rate and gaze, and yawning using the analysis module that is responsible for extraction of the visual features from the images taken by front camera. Rider interface is used to show to the rider determined dangerous state and recommendations. Recommendation module is responsible for generation of context-aware recommendations for the rider based on the detected dangerous situation and current situation in the road. Local database is responsible for storing a data collected by the smartphone. If the Internet connection is available, the smartphone uses the cloud to exchange useful information with other system users and to store generic information about the rider's behavior.

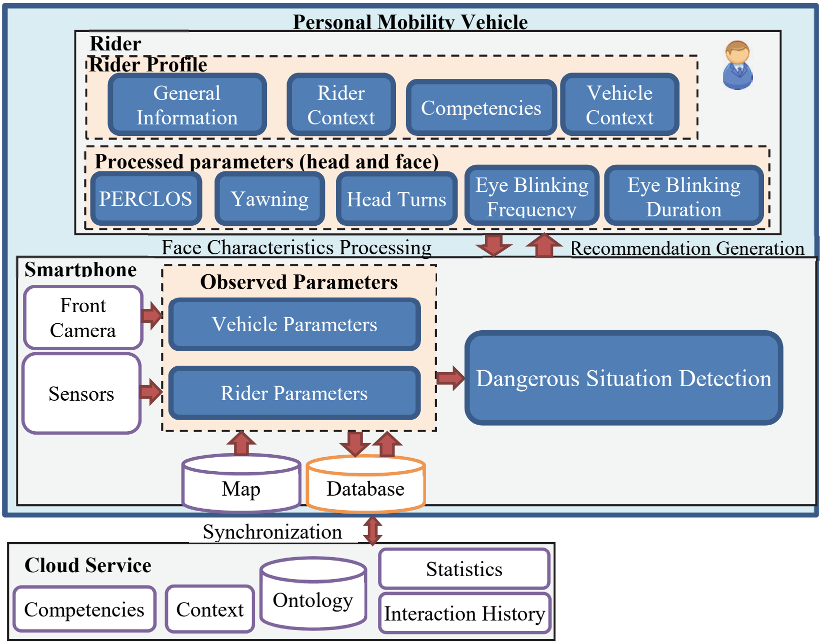



Fig. 1. An approach to dangerous situation detection

The following three main components are presented in Fig. : rider, smartphone, and cloud. Smartphone analyses the rider head and face and determine dangerous situations. Information for analyzing the rider head and face is collected by the mobile application component from the front camera using the image recognition. The application analyzes head movements (head rotation and nods), percentage of closure of eyelid (PERCLOS), eye blink rate and gaze, and yawning using the analysis module that is responsible for extraction of the visual features from the images taken by front camera. Rider interface is used to show to the rider determined dangerous state and recommendations. Recommendation module is responsible for generation of context-aware recommendations for the rider based on the detected dangerous situation and current situation in the road. Local database is responsible for storing a data collected by the smartphone. If the Internet connection is available, the smartphone uses the cloud to exchange useful information with other system users and to store generic information about the rider's behavior.

Such information as smartphone characteristics, application usage statistics, and dangerous events occurred during trip is stored for a deep analysis and using in the future. Smartphone characteristics are GPU, sensors (GPS, Accelerometer, Gyroscope, Magnetometer), front camera, memory & battery capacity, and version of operation system. The cloud is also used for keeping behavior patterns to analyze and create new dangerous situation.

The main function of the cloud service in the presented approach is the riding statistics accumulation and system behavior adaptation based on analysis of this statistics. In scope of the presented paper statistics of the determined distraction dangerous states as well as rider head rotation have been analyzed and compared with information of the PMD trajectory.

Rider assistant system accumulates statistics with the interval of every 0,1 sec. The system takes a frame from front-facing camera, recognize parameters of rider face and stores this information as well as information from smartphone sensors. To determine the dangerous situation the system monitors the rider for 2 seconds and in case of most of the analyzed frames confirm distraction dangerous situation the system recognize the dangerous state. The statistic example is presented in the Table 1. This statistic has been acquired is real situation. Accumulated statistics includes the following main parameters:

– event start time describes the date and time when the parameters have been recorded;

– trip start time specifies the date and time when the rider start his/her trip;

– situation start time specifies when the distraction dangerous situation has been started;

– latitude (lat) and longitude (long) specify the location of the rider at the moment of event fixation acquired from the smartphone GPS/GLONASS sensor;

– speed specifies the PMD speed at the moment at event fixation calculated based on latitude and longitude changes;

– acceleration specifies PMD acceleration parameter acquired from the smartphone accelerometer at the moment at event fixation;

– yaw and pitch angles specify the head rotation angles calculated from the frame acquired from the smartphone front-facing camera;

– situation processing time (ms) characterize the time that smartphone spent to recognize the dangerous situation;

– state parameter that characterize is the distraction dangerous situation has been recognized or not.

Table 1. Accumulated statistic example by the rider assistant system

| Event start time | Trip start time | Situation start time | Lat | Long | Speed | Acceleration | Yaw angle | Pitch angle | Situation processing time | State |
|---|---|---|---|---|---|---|---|---|---|---|
| 12.02.2019 5:16 | 12.02.2019 5:11 | 12.02.2019 5:16 | 59.949 | 30.246 | 15 | 13.82 | -22.76 | -10.26 | 1225 | Yes |
| 12.02.2019 5:16 | 12.02.2019 5:11 | 12.02.2019 5:16 | 59.949 | 30.246 | 15 | 13.82 | -20.32 | -9.44 | 1225 | Yes |
| 12.02.2019 5:16 | 12.02.2019 5:11 | 12.02.2019 5:16 | 59.949 | 30.246 | 15 | 13.82 | -14.82 | -7.71 | 1225 | Yes |
| 12.02.2019 5:16 | 12.02.2019 5:11 | 12.02.2019 5:16 | 59.949 | 30.246 | 15 | 13.82 | -11.41 | -6.28 | 1225 | Yes |
| 12.02.2019 5:16 | 12.02.2019 5:11 | 12.02.2019 5:16 | 59.949 | 30.246 | 15 | 13.82 | -10.45 | -8.63 | 1225 | Yes |
| 12.02.2019 5:23 | 12.02.2019 5:11 | | 59.953 | 30.267 | 68 | 13.82 | -9.98 | -8.12 | 1608 | No |
| 12.02.2019 5:23 | 12.02.2019 5:11 | | 59.954 | 30.267 | 68 | 13.82 | -15.41 | -10.49 | 1608 | No |
| 12.02.2019 5:23 | 12.02.2019 5:11 | | 59.954 | 30.267 | 68 | 11.77 | -4.1 | -11.51 | 1608 | No |
| 12.02.2019 5:23 | 12.02.2019 5:11 | | 59.954 | 30.267 | 68 | 11.77 | -2.62 | -11.24 | 1608 | No |
| 12.02.2019 5:23 | 12.02.2019 5:11 | | 59.954 | 30.267 | 68 | 11.77 | -3.86 | -8 | 1608 | No |
| 12.02.2019 5:23 | 12.02.2019 5:11 | | 59.954 | 30.267 | 68 | 11.77 | -3.7 | -8.44 | 1608 | No |

**4. Experiments.** In the experiment a Segway PMD (Segway Japan, http://www.segway-japan.net) and collected position information by Total Station range sensors by Lacia Geosystems (TM, R) is used. The first experiment is aimed at show how the person gaze is affected to the Segway PMD trajectory. The face direction angle of the subjects during the rides is recorded using the presented in the paper system. A smartphone has been plugged in to the Segway as shown in Figure 1 and has been synchronized with Total Station. The time synchronization error has been identified around one second. The experiments have been carried out in a gymnasium of Tsuruoka College to eliminate the effects of bumpy road and irregular road surfaces on the trajectories.

The experiment methodology is shown in Figure 2. There are four people participate in the experiments. Ages of the people are between 19 and 22 years old. Every person repeats the experiment seven times with a Segway PMD speed of 4 mile/h and travel the distance of 20 meters. For every people the following experiment has been conducted. A person should gaze to the target point while travelling from start position to the goal.

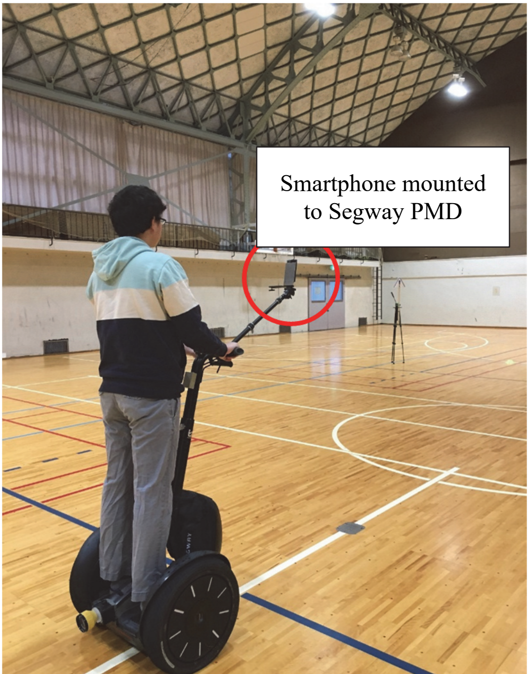



Fig. 1. Smartphone installed to the Segway PMD

The person travel along the y axis. The x-axis shows the lateral direction. The positive face direction angle (clockwise) is towards to the right side of the subjects and the negative vice versa to the left side. The scene of the experiment is shown in Figure 3. Experiment allows to identify how the people gaze is affected to the Segway PMD trajectory.

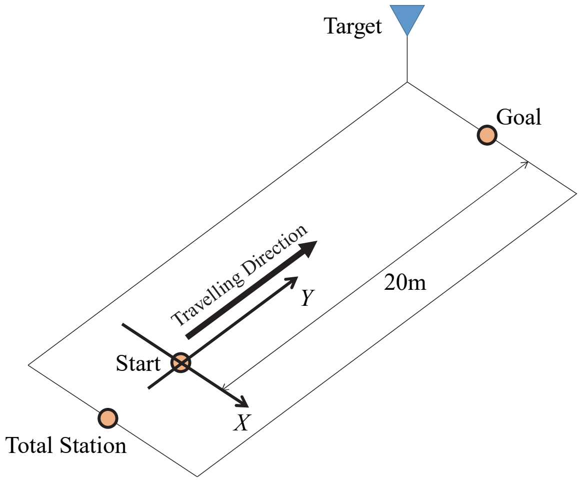
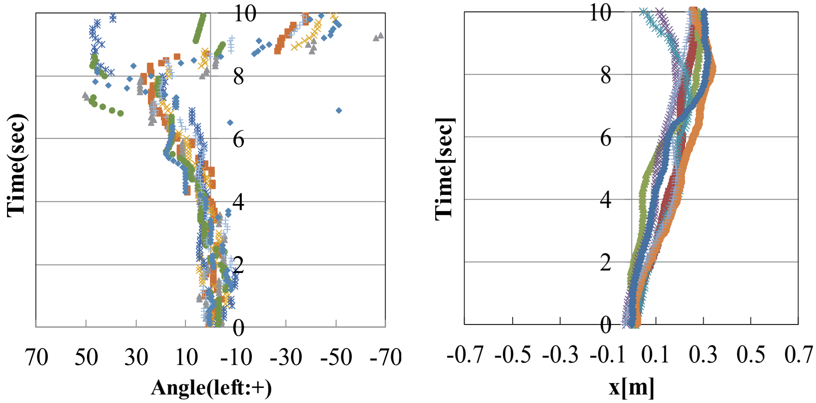



Fig. 2. Experiment methodology

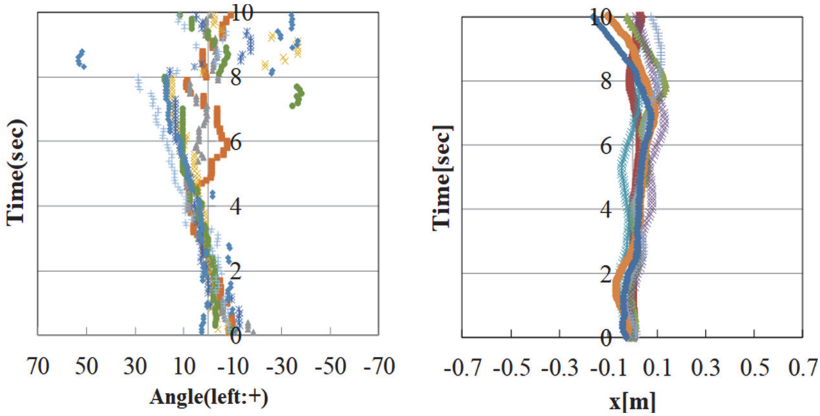
Fig. 3. Scene of the experiment

The face direction angle and trip trajectory have been measured analysed (see Figure 4 and 5 that show the face angle and the traveling trajectory in the experiments). In Figure 4(a), the horizontal axis is the face angle and the vertical axis is time. In Figure 4(b), the horizontal axis is the person lateral direction and the vertical axis is the time. The same situation for Figure 5.




a) b)

Fig. 4. Result of the first experiment for the person 1, (a) shows the face angle got by the proposed system and (b) shows the real angle measured by the Lacia Geosystems. Person 1 repeats the experiment seven times that is shown in the graphs




a) b)

Fig. 5. A result of the first experiment for the person 4, (a) shows the face angle got by the proposed system and (b) shows the real angle measured by the Lacia Geosystems. Person 4 repeats the experiment seven times that is shown in the graphs

As shown in Figure 4(a) the face angle increases as the user gazes to the target. Then, it shows that the deviation (error) in the lateral direction increases as the face angle increases. That is, it can be seen that a deviation occurs in the opposite direction to the gaze direction. Three other subjects confirm this tendency.

The experiments show that, there is a strong correlation between the face direction angle and the direction of the traveling trajectory. The deviation of the PMDs from the intended trajectory while the face direction changing create suspicion that the riders change the body centre of gravity without realizing it while gazing at the target.

The second experiment is aimed at show how making calls and text messaging are affected to the Segway PMD trajectory. The experiment is aimed at modelling the distracted person driving and track the trajectory. The experiment has been conducted both indoor and outdoor. There are 5 people participated and every person repeated the experiment 10 times for normal driving, driving and messaging, and driving and speaking by mobile phone. Figure 6-Figure15 show the results of the experiment for the people 1-5 both indoor and outdoor environments.

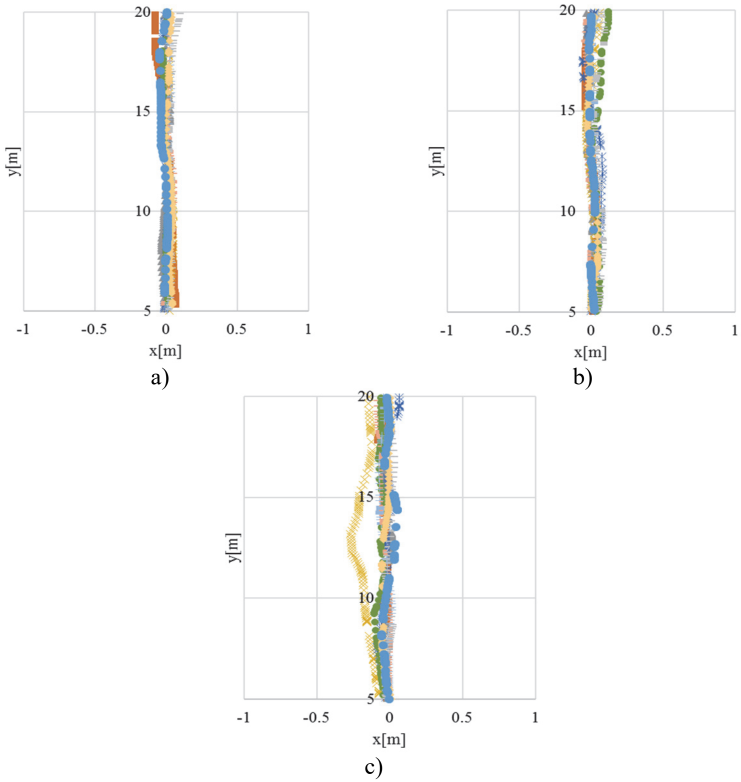
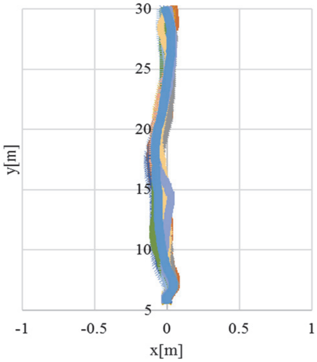
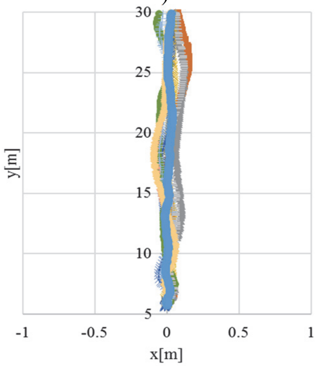


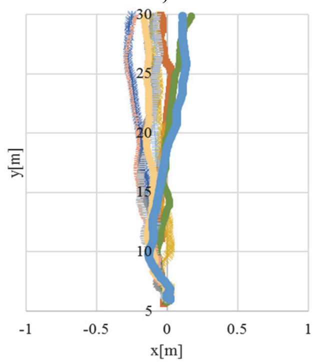

Fig. 6. A result of the second experiment for indoor environment conducted by person 1; (a) shows the normal riding, (b) represents the situation of riding and speaking by mobile phone; (c) shows the riding and messaging. Every experiment the person 1 repeats ten times that is shown in the Figures




a)

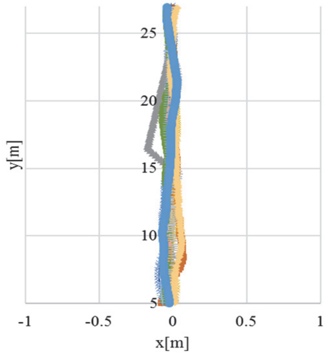



b)

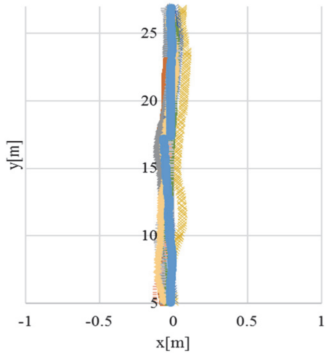



c)

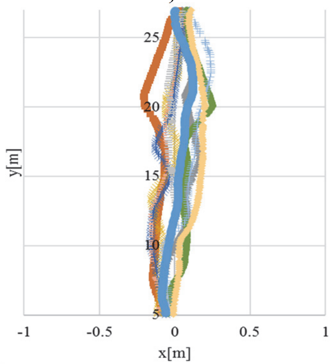
Fig. 7. A result of the second experiment for outdoor environment conducted by person 1; (a) shows the normal riding, (b) represents the situation of riding and speaking by mobile phone, and (c) shows the riding and messaging. Every experiment the person 1 repeats ten times that is shown in the Figures




a)

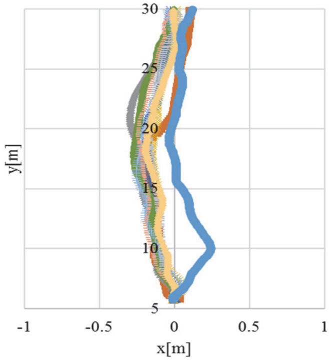



b)

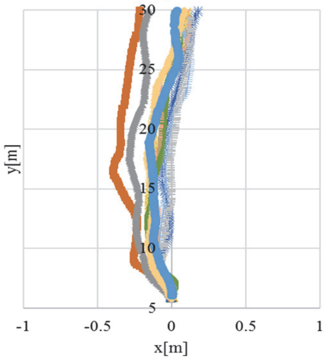



c)

Fig. 8. A result of the second experiment for indoor environment conducted by person 2; (a) shows the normal riding, (b) represents the situation of riding and speaking by mobile phone, and (c) shows the riding and messaging. Every experiment the person 2 repeats ten times that is shown in the Figures




a)

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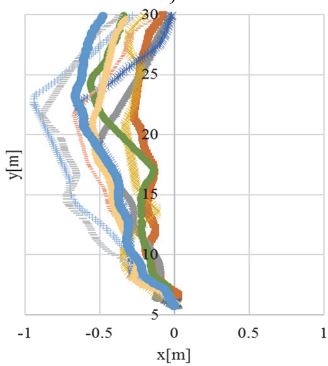
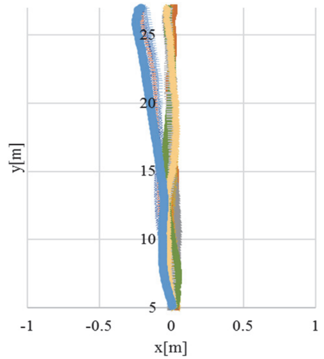
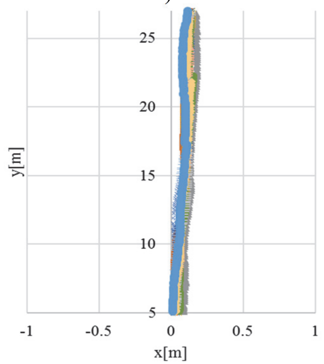



c)

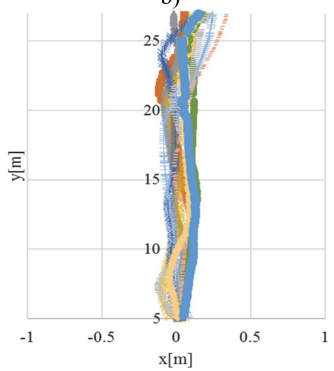
Fig. 9. A result of the second experiment for outdoor environment conducted by person 2; (a) shows the normal riding, (b) represents the situation of riding and speaking by mobile phone, and (c) shows the riding and messaging. Every experiment the person 2 repeats ten times that is shown in the Figures




a)

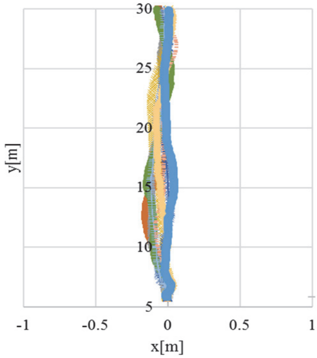



b)

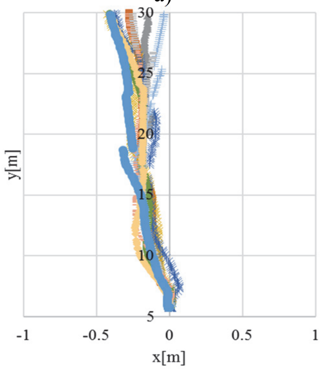



c)

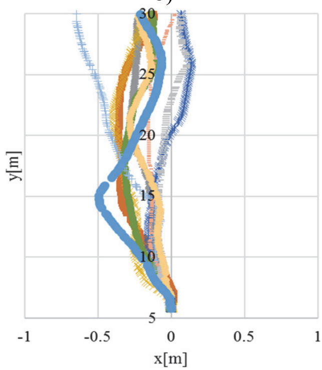
Fig. 10. A result of the second experiment for indoor environment conducted by person 3; (a) shows the normal riding, (b) represents the situation of riding and speaking by mobile phone, and (c) shows the riding and messaging. Every experiment the person 3 repeats ten times that is shown in the Figures




a)

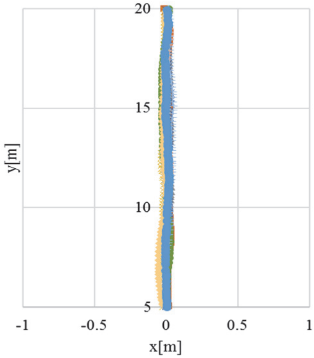



b)

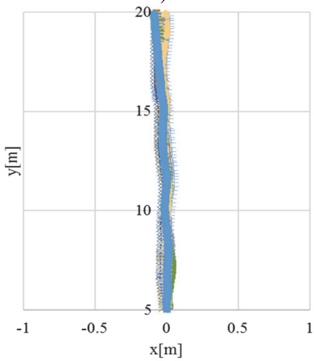



c)

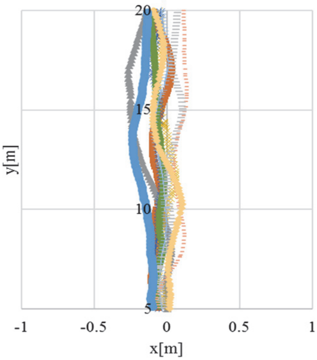
Fig. 11. A result of the second experiment for outdoor environment conducted by person 3; (a) shows the normal riding, (b) represents the situation of riding and speaking by mobile phone, and (c) shows the riding and messaging. Every experiment the person 3 repeats ten times that is shown in the Figures




a)

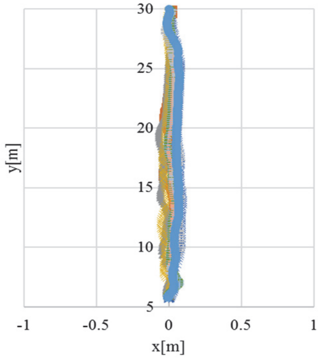



b)

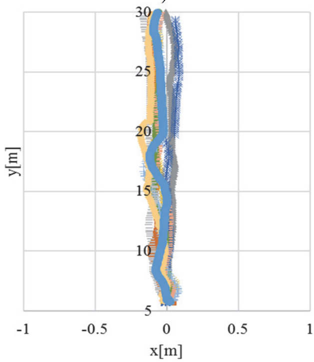



c)

Fig. 12. A result of the second experiment for indoor environment conducted by person 4; (a) shows the normal riding, (b) represents the situation of riding and speaking by mobile phone, and (c) shows the riding and messaging. Every experiment the person 4 repeats ten times that is shown in the Figures




a)

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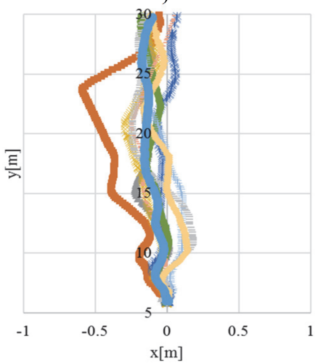
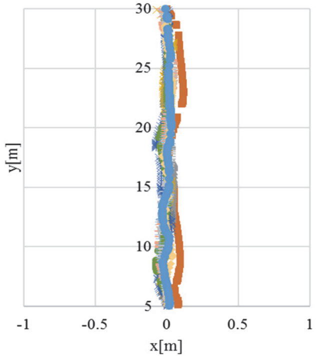
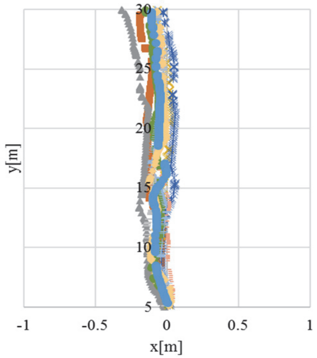



c)

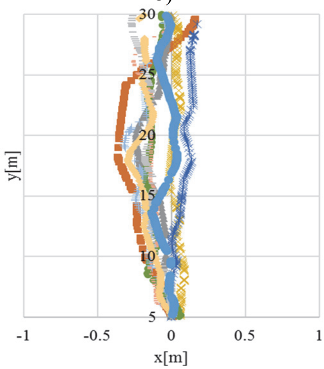
Fig. 13. A result of the second experiment for outdoor environment conducted by person 4; (a) shows the normal riding, (b) represents the situation of riding and speaking by mobile phone, and (c) shows the riding and messaging. Every experiment the person 4 repeats ten times that is shown in the Figures




a)

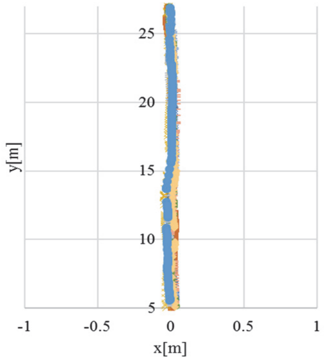



b)

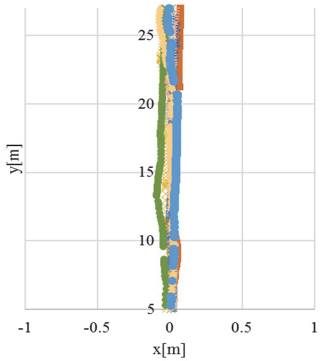



c)

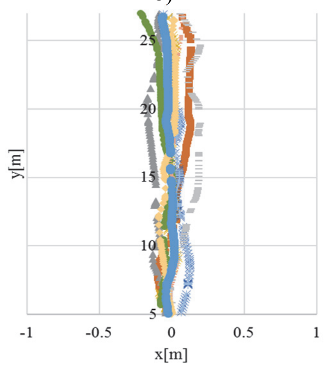
Fig. 14. A result of the second experiment for indoor environment conducted by person 5; (a) shows the normal riding, (b) represents the situation of riding and speaking by mobile phone, and (c) shows the riding and messaging. Every experiment the person 5 repeats ten times that is shown in the Figures




a)




b)




c)

Fig. 15. A result of the second experiment for outdoor environment conducted by person 5; (a) shows the normal riding, (b) represents the situation of riding and speaking by mobile phone, and (c) shows the riding and messaging. Every experiment the person 5 repeats ten times that is shown in the Figures

As it can be seen from the results the riding in outdoor environment has more lateral direction then compare with indoor. It can be concluded that outdoor environments have more possible distractions for the rider than indoor environments. Speaking by mobile phone affects small trajectory changes but lateral direction is not critical. Along with messaging during the riding causes the significant trajectory changes for all respondents in both: indoor and outdoor environments.

**5. Conclusion.** The paper presents context-based rider assistant system that is aimed at distraction dangerous situation recognition in real time and accumulate riding statistics in the cloud while riding PMD. The system initially has been developed for the car drivers and then adapted for the PMD riders. Using the system the experiments have been conducted that are aimed at studying the dependency of the Segway PMD trajectory based on rider distraction. There are two groups of experiments have been implemented. At the first group of experiments the rider move to one point and gaze to another one.

The head angle has been tracked by the presented rider assistant system while the Segway PMD trajectory has been tracked by the Lacia Geosystems (TM, R). At the second group of experiments it has been calculated the dependency of the Segway PMD trajectory based on people distraction. For the distraction the text messaging and phone calling situations have been considered. The experiments have been conducted for both: indoor and outdoor environment. Experiments show that Segway PMD trajectory is strongly depend on rider gaze. Also, the text messaging is the most dangerous situation while riding.

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# КОНТЕКСТНО-ОРИЕНТИРОВАННАЯ СИСТЕМА ИНФОРМАЦИОННОЙ ПОДДЕРЖКИ ОПЕРАТОРОВ ДВУХКОЛЕСНЫХ САМОБАЛАНСИРУЮЩИХСЯ ТРАНСПОРТНЫХ СРЕДСТВ

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**Аннотация.** Персональные мобильные устройства (гироскопы, двухколесные самобалансирующиеся транспортные средства, велосипеды и мотороллеры) в последние годы становятся все более популярными. Они помогают людям решать проблемы первой и последней мили в больших городах. Для того чтобы обеспечить оператору возможность навигации по городу, а также повысить его безопасность, предлагается использовать интеллектуальную систему помощи оператору с использованием персонального смартфона, который будет формировать контекст и предоставлять оператору рекомендации. Под контекстом в статье понимается любая информация, характеризующая текущую ситуацию. Предполагается, что оператор устанавливает персональный смартфон таким образом, чтобы фронтальная камера была направлена на его лицо. Таким образом, информация с фронтальной камеры и датчиков смартфона (GPS / ГЛОНАСС, акселерометр, гироскоп, магнитометр, микрофон) формирует контекст оператора. Представленная в статье система поддержки оператора ориентирована на обнаружение опасных ситуаций оператора персонального мобильного устройства: сонливость и невнимательность. Используя методы компьютерного зрения, предлагается определять параметры лица оператора (глаз, носа, рта, угла наклона и угла поворота головы) и на основании анализа этих параметров выявлять опасные ситуации. Представлен анализ современных исследований по интеллектуальным системам помощи водителям транспортных средств, предложен подход к обнаружению опасных ситуаций и генерации рекомендаций, а также проведены эксперименты с использованием предложенной системы и двухколесного самобалансирующегося транспортного средства.

**Ключевые слова:** контекст, поддержка оператора, транспортное средство, усталость, невнимательность.

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