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INTELLIGENT SYSTEM FOR DRIVER SUPPORT USING TWO CLASSIFIERS FOR SIMULATION

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ABSTRACT

The methodology of the study is based on the formulation and formalization of goals and objectives, the development of models, algorithmic methods, and experimental evaluation through experiments, testing, approbation and analysis of the results. In the work were used the methods of developing information systems to support the processes of collecting information, analyzing, designing and implementing such systems, the theory of algorithms for the effective formulation of subtasks and assessing the complexity of algorithms, the theory of machine learning for analyzing the behavior of drivers, generating recommendations for the driver to take measures to prevent the onset of an emergency and improve driving skills, as well as methods for developing software for the implementation of an intelligent accident prevention system. The goal of the work is to research and develop methods and algorithms for the operational control of the driver's condition, as well as the creation of a software video tracking system based on the developed algorithms. The main objectives of the work: 1) analysis of existing technologies, devices and active safety systems for the driver of a vehicle, focused on early warning and prevention of traffic accidents, as well as existing methods and algorithms for intelligent analysis of video surveillance data; 2) modeling using two classifiers and algorithms' development for improving driver real time safety; 3) development of an automated video tracking system using the proposed methods.

Keywords: *Driver safety, Image Processing, Automation, Transportation, Monitoring*

1. THE RELEVANCE OF DEVELOPING A DRIVER BEHAVIOR MONITORING SYSTEM

Road traffic crashes cause significant social and economic damage, affecting the health and lives of people around the world. In recent years, the damage from traffic accidents exceeds the damage from all other transport accidents (aircraft, ships, trains, etc.) combined [1]. Road traffic accidents are one of the major threats to the health and lives of people around the world. The problem is exacerbated by the fact that victims of accidents are, as a rule, young and healthy (before the accident) people. According to the World Health Organization [2, 3, 4], about 1.25 million people die every year in the world as a result of traffic accidents and up to 50 million receive non-fatal injuries. The number of road accidents caused by the state of fatigue or impaired attention [5] of the driver behind the wheel of a vehicle is growing every year and leads to injuries among the population around the world. Many drivers while driving a car experience a feeling of fatigue or impaired attention, and they do not even suspect that they are in such a state.

According to a report by the National Highway Traffic Safety Administration, up to nine percent of traffic accidents are caused by driver fatigue while driving a vehicle [6]. According to a study [7] by the AAA Foundation for Traffic Safety devoted to the analysis of driver behavior when driving in a half-asleep state, short sleep doubles the risk of an accident compared to those who slept the recommended seven or more hours. Drivers with less than four hours of sleep are 11.5 times more likely to be involved in an accident; from four to five hours - increases by 4.3 times; from five to six hours - by 1.9 times; from six to seven hours - 1.3 times. The study showed that a lack of sleep and, as a result, a slow reaction rate and a state of drowsiness can be just as dangerous as the state of alcohol intoxication – a slow reaction and a decrease in concentration.

As a solution to this problem, the scientific community proposed an approach to the development of active safety systems aimed at preventing accidents based on monitoring the behavior of the vehicle driver and timely notification of the driver about the current situation by generating context-oriented recommendations. The first studies of scientists on the systems for monitoring the environment and warning the driver development date back to 1992 [8]. Monitoring dangerous driving behavior [9, 10, 11, 12] can help to draw the attention of the driver to his driving style and the risks associated with it, thereby reducing the percentage of reckless driving and improving road safety skills.

Today, almost every new car delivered from the factory is equipped with some form of passive (for example, seat belts, airbags, etc.) and active (for example, anti-lock braking system, road stability system, in-line control system) movement, etc.) security [13, 14, 15, 16, 17, 18]. If passive safety systems are activated after the onset of an accident, then active ones come into action in advance and try to prevent or avoid a collision. The safety/ security systems discussed below will fall into the category of active safety/ security systems.

All security systems for monitoring the driver condition and the road situation can be divided according to the form of presentation into modern driver assistance systems, mobile recommendation generation systems, video cameras installed inside vehicles (car DVRs, separate video surveillance devices aimed at the driver or road) and wearable electronic devices (Figure 1).

Modern driver assistance systems are a class of systems that exist in the form of hardware and software complexes (cameras, sensors, sensors, chips, etc.) and are aimed at assisting the driver in order to prevent accidents or mitigate their consequences. These systems are installed in cars mainly at the factories of automakers.

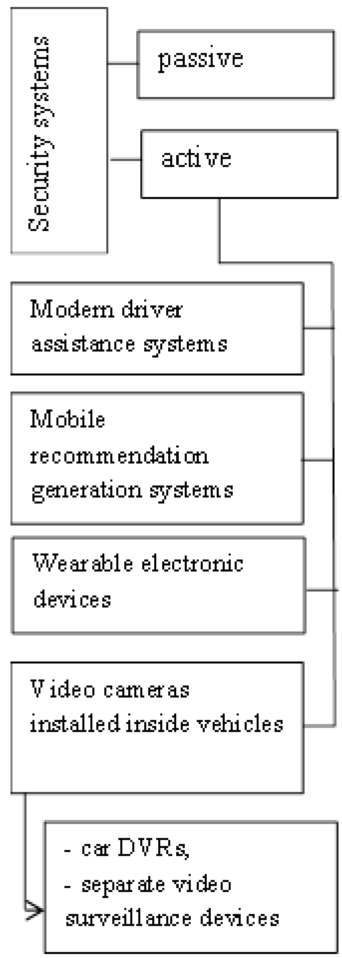

Figure 1: Systems for driver condition monitoring

High priority warning signals are provided by these systems to encourage vigilance and prompt and appropriate action by the driver in situations where serious injury or death may or may not be present or present. The technologies that make up modern driver assistance systems include such as a car lane keeping system, a speed warning system or a blind spot monitoring system. Despite the variety of integrated modern driver assistance systems in the automotive market, the high quality and speed of their work, one can single out significant drawbacks of integrated driver assistance systems: the cost of such systems remains quite high; available mainly as an additional option for expensive and exclusive cars.

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Taking into account the statistics [19, 20], the number of smartphone users by 2022 has exceeded 5 billion. We can judge the widespread use and availability of mobile devices (smartphones) among people around the world. Mobile recommendation generation systems are a category of driver safety systems that are developed on the basis of software solutions in the form of mobile applications and are subsequently installed on a smartphone from the application store (Google Play [21] for Android devices / Apple App Store [22] for iOS devices). One of the most popular mobile applications in the field of active safety systems is the iOnRoad solution [23]. The application uses the built-in camera, GPS and sensors to detect vehicles ahead and warn the driver in case of danger. This system captures objects in front of the driver in real time, calculating the current speed using sensors. When danger is imminent, the Audible and Graphical Collision Warning of the Active Safety System pops up, allowing the driver to brake in time.

It should be noted that mobile applications have a number of disadvantages. The main one is that mobile applications cannot interfere with the vehicle control process and thus respond faster to emergencies that occur while driving. Another disadvantage of such solutions is that the accuracy of recognition of dangerous conditions is noticeably lower compared to driver assistance systems.

Car DVRs, video surveillance devices and wearable electronics devices in comparison with driver assistance systems are a more affordable option for using active safety systems. In the first case, the internal video cameras use the processor and the camera to monitor only the situation in front of the vehicle, realizing such functions as, for example, lane departure control. In this case, the camera independently controls the road markings and plays a sound signal if the car crosses the markings. So, for example, some models of video recorders from Garmin [24] can make not only video recording of the traffic situation, but also control over the safety of the vehicle, including the functions of warning about leaving the lane or about unsafe approach to the vehicle in front. A review of wearable electronics showed that this category of devices is aimed at the vehicle cabin and monitors the driver's behavior. Taking an electromyogram and an electroencephalogram of a driver in real time or fixing a change in the galvanic skin response (GSR) [25], wearable electronic devices measure the degree of driver drowsiness, warning him in advance with the help of sound and vibration signals.

One example of such devices is a wrist bracelet with built-in sensor, manufactured by Neurocom [26], as well as [27, 28] to maintain the driver's performance by detecting the onset of his state of drowsiness based on the results of measurements of the galvanic skin response (GSR) and early warning of approaching a potentially hazardous situation.

Technologies for improving active safety have become widespread in the form of integrated software and hardware systems for improving driver safety in vehicles. Despite the fact that driver assistance systems make it possible to achieve high accuracy, completeness and speed of recognition of unsafe traffic situations through the use of multi-camera systems together with radars and laser rangefinders, such systems remain inaccessible for a large number of vehicles, and their cost is high compared to mobile recommendation generation systems, video recorders and wearable electronics devices. The use of algorithms for personalizing the behavior and driving style of a particular driver based on vehicle control statistics using a remote service will expand the capabilities of mobile recommendation generation systems and develop an intelligent emergency warning system that takes into account information about the driver profile, vehicle, current context, and previous experience of using the system. and statistics of interaction between other participants and the system, which in turn distinguishes this solution from existing video recorders and wearable electronics devices. Among the possible options for integrating this system, one can single out the on-board system of the car and a mobile application on a smartphone. It should be noted that the integration of an intelligent system into the on-board vehicle system at the production stage is an expensive and time-consuming process that affects suppliers of automotive components, and sometimes it is simply not available due to a number of restrictions by automakers.

Road safety is determined not only by road conditions, the technical condition of vehicles and compliance with traffic rules, but also by the skills, physical condition, ability to concentrate and compliance with safety measures by drivers [29, 30].

World manufacturers of cars and trucks are developing a separate class of modern systems for tracking the driver's condition and traffic conditions [31, 32] as a driver assistance system, which is hardware and software system that can increase the level of traffic safety on public roads. Vehicles equipped with driver assistance systems are an intermediate link between conventional driver-controlled vehicles and vehicles equipped with an automatic control system. The functions of driver assistance systems can be classified as follows:

- adaptive systems that change (adapt) based on input data from the external environment;
- automated systems that perform functions that the driver cannot safely perform;
- monitoring systems that use sensors, cameras and other means in their work to monitor the space around the car and decide whether intervention in driving is necessary;
- warning systems that notify the driver of potential emergency situations while driving.

The scheme of the active safety system operation with a high-priority warning to the driver in the general case can be described by the following sequence of "perception-response" commands: detection of the possibility of a collision of the vehicle, the system displays information about a possible collision in the absence of an appropriate reaction from the driver, notification of an emergency using a warning signal and development of recommendations to prevent the onset of an accident, attracting the driver's attention, the driver's awareness (identification) of an ongoing emergency situation, the choice of a solution, the driver's response and taking measures to prevent an accident.

The most common technologies that make up modern driver assistance systems can be identified:

- technology of blind zones control;
- Lane Departure Warning technology that calculates the time until lane crossing and alerts the driver if lane departure is detected;
- pedestrian and cyclist detection technology;
- traffic sign recognition technology;
- forward collision warning and crash mitigation technology;
- technology for monitoring compliance with a safe distance.

These systems are designed to help drivers of vehicles prevent the onset of a traffic accident or mitigate its consequences in advance.

Today there are a lot of researches in the field of computer vision (for example, [36, 37, 38, 39]). In driver assistance systems, the non-verbal expression of the internal state by the driver of the vehicle is analyzed using a video camera by observing his head and face, which provide sufficiently accurate characteristics that can be used to determine the physiological characteristics of the driver. So, for example, driving a car requires the driver to fully concentrate, respond well and adequately perceive the traffic situation. There are a large number of driver distractions such as phone calls, SMS messages, multimedia and navigation systems. If the driver is distracted from the traffic situation while the vehicle is in motion, the driver assistance system will inform the driver about the onset of a dangerous situation and the existing risk of an accident. In this case, the driver has time to perform the necessary maneuver to avoid a traffic accident.

The technologies that make up the systems for improving driver safety can be conditionally divided according to the type of context into those that monitor the environment (traffic situation) and those that are aimed at monitoring the behavior of the driver inside the vehicle cabin. Any information that is relevant in describing the situation in which some object (driver, vehicle) is located at a certain point in time is used as a context.

Modern implementations of driver assistance systems are available to some extent in the factory equipment of new cars, and some of them are purchased and installed separately. It should be noted that such technologies are not available for all vehicles, and the price range of such solutions remains quite high. Unlike driver assistance systems, mobile recommendation generation systems require the driver only to have a mid-price smartphone with a mobile application installed on it, which implements the functions of increasing the safety of the driver's behavior while driving, which allows the use of driver behavior and traffic monitoring systems in any vehicle. Existing mobile software systems are severely limited in their ability to recognize emergency situations while driving; none of these solutions fully evaluates the behavior of the driver behind the wheel inside the vehicle cabin.

According such statistics, much attention is now being paid to the development of technical systems for monitoring the level of dangerous

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functional states of a person, united by the term “fatigue monitoring devices”, aimed at detecting and preventing such conditions [13, 14, 21, 32, 38, 39].

Table 1: Comparison of existing systems

Existing systems	Electronic anti-sleep alarm StopSleep	Driver sleepiness detection Bosch	Anti-sleep Pilot
1	2	3	4
Developer	StopSleep PLC	Bosch, Germany	ASP technology Ltd, Denmark
Detection method	Skin warmth	Steering patterns	Driver reactions to random tests
Hardware devices	8 sensors	Steering angle sensors	Light, sound and touch sensors
Device type	Portable	Not portable	Not portable
Alert method	Device vibration, output light and sound	Flashing coffee cup sign in the system	Sound
Approxi-mate price, USD	200	-	250

Table 2: Comparison of existing systems

Existing systems	Lane Departure Warning System	Drowsiness detection system using electroence phalograph y helmets	Tesla Auto Pilot
1	2	3	4
Developer	Mercedes Menz	Ford Motor Co	Tesla Inc.
Detection method	Lane borders	Alpha activity of the human brain	Control of obstacles around the car
Hardware devices	Camera	Electroence phalograph y helmet	8 cameras and 12 ultrasound sensors
Device type	Not portable	Portable	Not portable
Alert method	Flashing light and sound	Steering wheel vibration with sound	Driving a car without human intervention
Approxi-mate price, USD	1000 and more	500-1000	80000

Currently, there are several dozen such systems based on the use of various physiological and behavioral indicators, but they still have a limited scope and insufficient efficiency [13, 14, 38, 39], associated with the probabilistic nature of the occurrence of behavioral errors with a decrease in the level of wakefulness. [19, 24, 25] (Table 1 and Table 2).

However, an increase in the need for sleep is accompanied by an increase in the instability of behavioral responses [19, 39]. So-called "dips" in activity, called "micro-sleep", may suddenly occur, after which the reaction time quickly returns to its original values. [15, 26]. This phenomenon was formulated in the form of the “state of instability” hypothesis in attention [19, 24, 25, 39].

In some studies, when analyzing activity disorders, they do not speak about the onset of the “moment of sleep” [23, 33, 34, 35], but more correctly assess the probability of occurrence of episodes of “micro-sleep” and accompanying errors in activity [5, 13, 25]. It is assumed that the occurrence of a drowsy state of consciousness during long-term monotonous driving along a straight road causes the absence of subjective perception by the driver of the danger of his reduced level of wakefulness [7, 23, 29, 30].

Thus, the development of a driver behavior monitoring system that determines the dangerous state of the driver in the vehicle cabin and warns him about the possibility of an emergency situation using a smartphone is an urgent and demanded task.

2. MODELING AND ALGORITHMS’ DEVELOPMENT

We will use video analytics, the main task of which is to detect moving objects in a video stream to recognize the fatigue of a vehicle driver. The task of detecting a face in an image (face detection) is one of the most important tasks solved by computer vision systems. However, when trying to build an automatic face detection system, one has to face the following factors that complicate the detection process:

- individual features of facial features of different people complicate the choice of signs of objects of detection;
- a slight change in the orientation of the face relative to the camera entails a major change in the image of the face;
- part of the face may be invisible (covered by other objects) in the image;

- shooting conditions (lighting, camera color balance, image distortion, image quality) greatly affect the image.

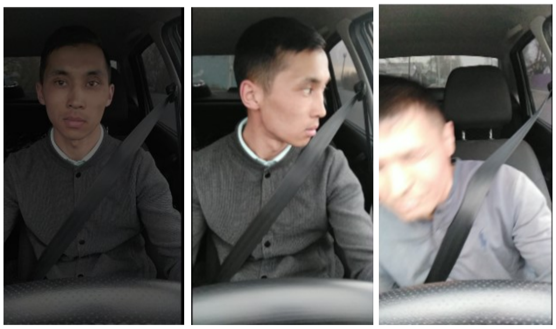

Figure 2: Poor lighting - Facial orientation change - Poor image quality

According these reasons, there is a need to continue training on new images of objects in the problem of face detection, i.e. dynamic learning process (on-line learning). The main advantage of vision systems using this kind of training is an increase in detection efficiency, since over time the algorithm makes fewer errors on new objects. After detecting the next object, the algorithm is given the class label of this object, which it must take into account, i.e., "learn more".

The Viola-Jones method is known for face detection in a frame of a video stream [40, 41]. In our work, we propose a way to improve the quality of the algorithms for detecting moving objects in a video stream by adapting them to changing scene characteristics and new images of objects. The algorithm is based on the composition of the Viola-Jones method and Incremental Learning Support Vector Machine.

Let there be a video sequence, which is a sequence of frames. Each frame is a digital image and is a two-dimensional matrix of pixels At with size m×n. Each pixel, if the image is black and white, is a non-negative number between 0 and 255; where t is the frame number in the video sequence. Unlike static images, working with video allows you to highlight the area of motion, thereby reducing the size of the search area.

After selecting the area of motion by cutting out from the matrix At, we obtain the matrix Ct. The size of Ct is equal to $w_C \times h_C$, where $w_C \leq m$ и $h_C \leq n$.

Based on the motion area, it is required to determine, if it exists, a list of rectangles containing a person's face:

$$\mathbf{Face}_i = \{x_i, y_i, w_i, h_i\}, \quad (1)$$

where x_i, y_i – are the coordinates of the center of the i-th rectangle, w_i – is the width, h_i – is the height.

The search for an object will be performed by a "scanning window" of width W and height H, passing sequentially over the image with a step of 1 pixel (left to right, top to bottom) with a change in scale with each pass (Figure 3).

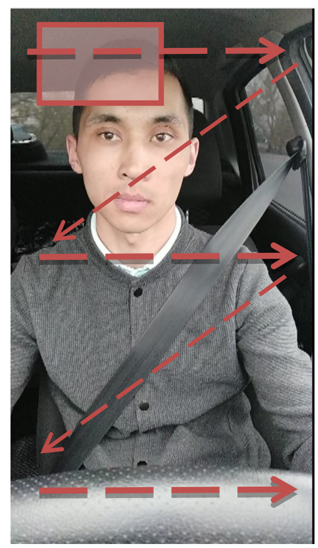

Figure 3: "Scanning window"

By assigning the analyzed part of the image to one of two classes (presence of a face / absence), when passing the scanning window through the image, it is necessary to determine whether the window contains a face or not for each position of the window:

{"non-face"; "face"}={-1;+1}

Thus, the problem of face detection in a video stream frame is reduced to a two-class classification problem. The traditional formulation of the recognition problem will look like this.

It is given:

X – is a set of indicative descriptions of objects,
Y – is a finite set of classes.
F – is the decision function *F*:**X**→**Y**.
Feature *f* of object *a* is a mapping *f*:**X**→**Df**, where **Df** – is the set of admissible values of feature *f*.

If a set of features *f1,…, fr* is given for some object *a*, then the feature vector **x** of the object $a \in \mathbf{X}$ can be defined as follows [40, 41]:

$$\mathbf{x}=\left(f_1(a),\dots,f_r(a)\right). \quad (2)$$

In this case, the feature vector can be identified with the objects themselves.

The classifier *F* must be able to classify an arbitrary object $a \in \mathbf{X}$. The classifier that gives the least error probability for all admissible values of **x** is considered optimal.

A training sample is used to train the classifier *F* given by the set:

$$\mathbf{D}=\{(\mathbf{x}_1,y_1),\dots,(\mathbf{x}_m,y_m)\},$$ where $$y_i \in \mathbf{Y}=\{-1;+1\}. \quad (3)$$

We propose the joint use of two classifiers: the first of them is built on the basis of the Viola-Jones method pre-trained and has proven itself well in most software products [40, 41]; the second classifier must support online learning. The second classifier will be trained as follows:

1. An external camera calibration is performed, which allows you to determine such parameters as: camera tilt angles, installation height, lighting conditions.

2. If the images parameters correspond to or are close to ideal, that is, the tilt angles are insignificant, the illumination is bright, then there is no need to use a second classifier. Detection is performed only by a classifier built on the basis of the Viola-Jones method.

3. If the shooting conditions are different from the ideal ones, then based on the parameters, the images that are closest to these conditions are selected from the pre-formed database of standards, thus, a training sample is formed taking into account the shooting conditions.

4. The resulting sample is used to train the second classifier.

5. During the operation of the algorithm, all the images obtained by the second classifier are also used to retrain the classifier.

The image entering the classifier can be characterized by the following features that affect the quality of the algorithm:

- tilt angles and turns of the face;
- camera installation height and inclination angle relative to the surface plane;
- lighting level;
- face scale relative to image size;
- noisy image.

Figure 4: Examples of images taken under different conditions; a) - an ideal image; b) - image in real conditions

Let us introduce the following notation for a number of parameters of the processed image:

α_h – lateral tilt of the face relative to the vertical axis,

α_v – rotation of the face relative to the vertical axis,

α_z – frontal head tilt angle (depending on the installation height and camera tilt angle),

Lht – scene illumination level,

Nos – image noise level (0 – ideal image, 1 – infinitely corrupted image).

Let's move on to the relative values {0; 1} for the convenience of calculations, for this it is necessary to set threshold values for each of the characteristics. It is permissible to take modulo values for the parameters characterizing tilts and turns of the face considering that the object of detection is symmetrical. Face detection is the first step in solving a more complex problem - face identification (recognition).

The impact of external conditions on the object *a* is expressed as follows:

$$\mathbf{Q(a)}=(\alpha_h,\ \alpha_v,\ \alpha_z,\ Lht,\ Nos). \quad (4)$$

The training sample is represented by a set of objects with labels of their classes, and then any training/testing sample consisting of n images can be described by the following vector:

$$\mathbf{D} = \{\boldsymbol{Q}(a_1),\ \boldsymbol{Q}(a_2),\dots\ \boldsymbol{Q}(a_n)\} =$$

$$= \{(\alpha_{h1}, \alpha_{v1}, \alpha_{z1}, Lht_1, Nos_1), \ldots(\alpha_{hn}, \alpha_{vn}, \alpha_{zn}, Lht_n, Nos_n)\} . \quad (5)$$

Let's move on to the next entry for parametric estimation of the training sample:

$$\mathbf{D} = \{(\alpha_{h1}, \ldots \alpha_{hn}),(\alpha_{v1}, \ldots \alpha_{vn}), (\alpha_{z1}, \ldots \alpha_{zn}),(Lht_1, \ldots Lht_n), (Nos_1 \ldots Nos_n)\}. \quad (6)$$

We can build the distribution of the number of images by the value of the parameter for each of the characteristics. The values that occur most often will be called the mode. As a result of calculating the mode for each of the parameters, we can describe the training set as follows:

$$M_D = \{M\alpha_h, M\alpha_v, M\alpha_z, M_{Lht}, M_{Nos}\}, \quad (7)$$

where $M\alpha_h, M\alpha_v, M\alpha_z, M_{Lht}, M_{Nos}$ – mode for each parameter.

The M_D vector will describe the most common image parameters in the sample.

The minimum and maximum values of the image parameters in the sample are determined as follows:

$$D_{min}^{max} = \begin{Bmatrix} (min_{a_h}, max_{a_h}), (min_{a_v}, max_{a_v}), \\ (min_{a_z}, max_{a_z}), (min_{Lht}, max_{Lht}), \\ (min_{Nos}, max_{Nos}) \end{Bmatrix}$$

$$M_D = (0, 0, 0, 0, 0). \quad (8)$$

Thus, we can conclude that for the successful operation of the classifier, it is necessary that the characteristics of the testing images be within D_{min}^{max}. Obviously, the closer the M_D plots of the testing sample and the training sample, the higher the result of the classifier. In practice, this is difficult to implement, since the training sample must contain the most common variations of images obtained from a particular surveillance camera on which the classifier will work.

Since the Viola-Jones classifier does not support retraining, it is necessary to use a second classifier that is not inferior in quality to the Viola-Jones method and will support online learning. Such a classifier is the support vector machine [38, 42]. The main problem is the need for preliminary training of the SVM classifier on a small number of images. Moreover, these images must correspond in terms of parameters to the image of the scene. Based on this, the task is to determine the image parameters or external calibration.

The external camera calibration [42, 43, 44, 45] is used to determine the orientation and location of the camera in space, i.e. to determine the angles of inclination and rotation of the camera.

The calibration process is based on information about the objects that are captured by the camera: their proportions, orientation, and spatial position.

It is known, an image is a display of a scene on a plane. The model of the visual system of the surveillance camera (Figure 5) consists of:

1. Rectangular image coordinate system with integer R and C axes, where R and C coordinates are the numbers of rows and columns of pixels in the image.

2. Rectangular camera coordinate system with real axes Xc, Yc, Zc.

3. Rectangular world coordinate system with real axes Xw, Yw, Zw.

The optical center in the camera system has coordinates (0, -f, 0). The image plane RC, modeling the camera matrix, lies in the XcYc plane, and the Zc axis is the optical axis of the camera.

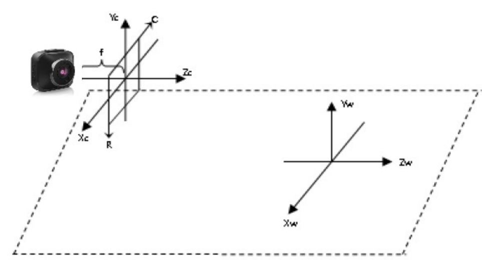

Figure 5: The model of the visual system of the surveillance camera

The task of camera calibration is to determine how the pixels are located on the image plane of a given camera relative to the points of three-dimensional space, the images of which are to be obtained using the camera. This problem is solved by defining a camera model C_W^I, which allows you to match any point in space (x^w, y^w, z^w), given in the world coordinate system, with a point on the image (r,c) with an arbitrary scaling element *s*:

$$\begin{bmatrix} s\cdot r \\ s\cdot c \\ s \end{bmatrix} = \mathbf{C}_W^I \begin{bmatrix} x^w \\ y^w \\ z^w \\ 1 \end{bmatrix}. \quad (9)$$

External parameters describe the location and orientation of the camera's coordinate system in the world coordinate system. These options include:
- transfer parameters: $\mathbf{t}=[t_x, t_y, t_z]^T$;
- rotation parameters:

$$\mathbf{R}=\begin{bmatrix} r_{11} & r_{12} & r_{13} & 0 \\ r_{21} & r_{22} & r_{23} & 0 \\ r_{31} & r_{32} & r_{33} & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}. \quad (10)$$

The transfer parameters describe the location of the camera in the world coordinate system, and the rotation parameters describe its orientation.

The matrix **R** can be represented as a product of three rotation matrices:

$$\mathbf{R}=\mathbf{R}_{ox}\mathbf{R}_{oy}\mathbf{R}_{oz}.$$

$$\mathbf{R}_{ox}=\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos\alpha & -\sin\alpha & 0 \\ 0 & \sin\alpha & \cos\alpha & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

$$\mathbf{R}_{oy}=\begin{bmatrix} \cos\beta & 0 & \sin\beta & 0 \\ 0 & 1 & 0 & 0 \\ -\sin\beta & 0 & \cos\beta & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

$$\mathbf{R}_{oz}=\begin{bmatrix} \cos\gamma & -\sin\gamma & 0 & 0 \\ \sin\gamma & \cos\gamma & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad (11)$$

where $\mathbf{R}_{ox}$ – rotation matrix around the *OX* axis by the angle *α*, $\mathbf{R}_{oy}$ – rotation matrix around the *OY* axis by the angle *β*, $\mathbf{R}_{oz}$ – rotation matrix around the *OZ* axis by the angle *γ*:

Thus, in fact, there are only 3 independent rotation parameters: *α, β, γ*.

The transformation from the world coordinate system to the camera system depends only on external parameters and has the form:

$$\mathbf{T}_w^C=\begin{bmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad \begin{bmatrix} x^c \\ y^c \\ z^c \\ 1 \end{bmatrix} = \mathbf{T}_w^C \begin{bmatrix} x^w \\ y^w \\ z^w \\ 1 \end{bmatrix}. \quad (12)$$

The transformation T_W^C is reversible: $\mathbf{T}_C^W=(\mathbf{T}_W^C)^{-1}$.

Transform composition $\mathbf{T}_C^I$ and $\mathbf{T}_W^C$ is the camera $\mathbf{C}_W^I$ model:

$$\mathbf{C}_W^I=\mathbf{T}_C^I\mathbf{T}_W^C. \quad (13)$$

The approach proposed and described in detail in [43] to automate external parameters is used. Studies [46-53] are also taken into account.

3. AN AUTOMATED VIDEO TRACKING SYSTEM DEVELOPMENT

The functional scheme of the system for driver condition assessing will consist of the following main stages:

1) Capture video from the camera.
2) Getting the input image.
3) Pre-processing stage.
4) Face and eyes in the image detection.
5) Stage of evaluation detection using a cascade classifier.
6) Evaluation of eyes opening/closing.
7) Alert.

The pre-processing step consists of two different processes:
- Face and eye detection stage;
- Image processing.

The camera will capture the image of the driver and, through a pre-processing stage, determine the face and eyes of the driver. At this stage, image processing algorithms are used to convert the live video stream into a sequence of digital images. After conversion, the system will

Journal of Theoretical and Applied Information Technology
15th August 2022. Vol.100. No 15

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pass these images to the next stage: determining the position of the face and eyes.

During face and eye detection, the camera will capture live video. The video stream is a sequence of image frames, and in this process, all image frames are different from the video stream. Each of the image frames is converted to gray images (also known as gray scaling) so that noise is removed from the color images and this makes the images easier to compute. Gray scaling will also eliminate any unwanted color channels, therefore reducing image processing time. Once the images have been converted to grayscale images, the simulation uses the existing HaarCascade face and eye datasets to process the grayscale images for face and open eye detection. It first tries to detect a face in the image, and if the simulator can't detect a face, it grabs the next frame of the image while incrementing the "number of closed eyes" variable. If a face is detected, the system verifies that the number of detected faces is exactly one. This is because we are not interested in multiple face detection in this particular model. When a face is detected, the simulation will start detecting both the left eye and the right eye. If no eyes are detected, the "eyes closed" variable is incremented and it moves to the next image frame in the sequence. If both eyes are detected, the system will draw a rectangular box around the face as well as the eyes to indicate that the system has detected eyes (Figure 6).

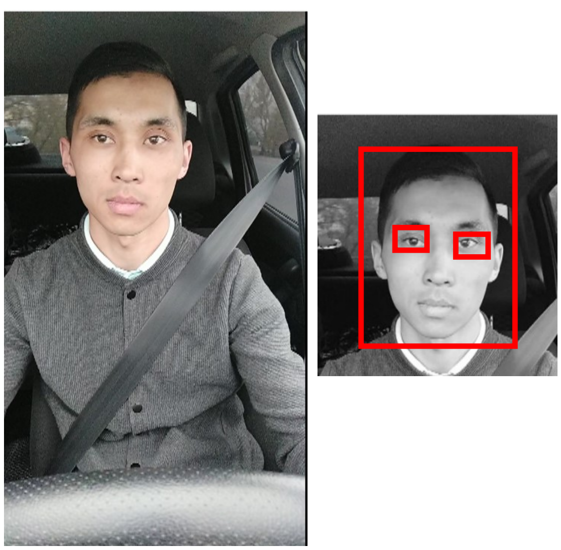

Figure 6: Face and eyes detection

On the stage of the face and eye positioning, the driver sleepiness detection system will use the Haar Cascade classifier to determine the exact position of the face and eyes in the image. We will use the trained Haar Cascade Classifier dataset for object recognition. Two different processes based on the Haar Cascade for face and eye detection will be involved:

- face recognition in the photo;
- detection of eyes on the face.

After these processes, these images will be transferred to the next stage of the system.

During the evaluation detection stage, the proposed system will determine the condition of the eyes. The system determines whether the eyes are open or closed. If the eyelids are closed, the iris (the dark area of the eye) will be invisible and this will be recognized as a closed eye condition. Considering the scenario, the system will alert the driver with a sound if the eye closure percentage is higher than the detection percentage provided by the driver.

The process of generating warnings is done in a separate thread in the simulation. It first checks if the current seconds spent in the process are equal to the warning sequence selected by the driver. If not, then the simulation does nothing. But if it is the driver's chosen warning sequence, then the simulation calculates the actual percentage of closed eyes for that time sequence, as shown below. Actual eye-closed percentage (%) = (eye-closed frames / total frames) * 100 .

If the actual closed eye percentage is greater than or equal to the user closed eye percentage set by the driver, an alarm is generated. Otherwise, the alarm will be stopped. Last but not least, the system will also write all driver statistics to a file as an added value so that this data can be used for machine learning purposes as future improvements to this simulation.

Classification of the eye condition is carried out using computer vision methods using an algorithm implemented in PYTHON. Let us calculate the ratio of the distances between the vertical features of the eye and the distances between the horizontal features of the eye. This requires calculating the Euclidean distances between two sets of vertical and horizontal features of the eye (x, y)-coordinates:

Journal of Theoretical and Applied Information Technology
15th August 2022. Vol.100. No 15

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

```
def findEAR(eye):
A = dist.euclidean (eye[1], eye [5])
B = dist.euclidean (eye[2], eye [4])
C = dist.euclidean (eye[0], eye [3])
ear = (A + B) / (2.0 * C)
return ear
```

The returned value for the aspect ratio of the eye will be approximately constant and positive when the eye is open. The value will then quickly decrease to zero while blinking.

If the eye is closed, the aspect ratio of the eye will again remain roughly constant, but will be much smaller than the ratio at the time the eye is open. Visualization is shown in Figure 7.

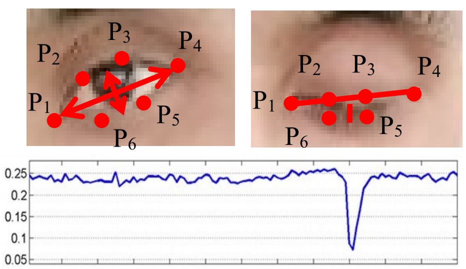

Figure 7: Visualization of eye landmarks. Top left: eye open. Top right: Eye closed. Bottom: Plot of aspect ratio over time. A drop in the aspect ratio of the eye indicates blinking.

The aspect ratio of the eyes should be monitored to see if this value drops, but also increases again, which would indicate that the driver has closed his eyes for detector development. Next, the following variables are defined for the thresholds:

- two constants: for the aspect ratio of the eye to determine blinking and for the number of consecutive frames;

- the number of frames of closed eyes must be below the threshold value THRESHOLD_EAR for the alarm to be triggered;

- initialize the frame counter COUNTER – the total number of consecutive frames during which the aspect ratio of the eye is less than THRESHOLD_EAR, as well as a logical value for indicating an alarm.

```
THRESHOLD_EAR = 0.3
FRAMES_EAR = 48
COUNTER = 0
ALARM_ON = False
```

It is necessary to start counting the number of frames during which the person closed his eyes if the aspect ratio of the eye falls below the THRESHOLD_EAR threshold.

If the number of frames in which the person closed their eyes exceeds FRAMES_EAR, then a beep should be emitted.

If a person closes their eyes for 48 consecutive frames, an audible signal will be played. It is possible to make the detector more sensitive by decreasing FRAMES_EAR – similarly, less sensitive by increasing it. If COUNTER is greater than FRAMES_EAR, then update the boolean ALARM_ON.

We use the dlib library and a face detector based on a histogram of oriented gradients along with a facial feature predictor.

```
detector = dlib.get_frontal_face_detector()
predictor = dlib.shape_predictor(args["shape_predictor"])
```

Let's allocate indexes of signs of eyes:

```
(leftEyeSt, leftEyeEnd) = face_utils.FACIAL_LANDMARKS_IDXS["left_eye"]
(rightEyeSt, rightEyeEnd) = face_utils. FACIAL_LANDMARKS_IDXS["right_eye"]
```

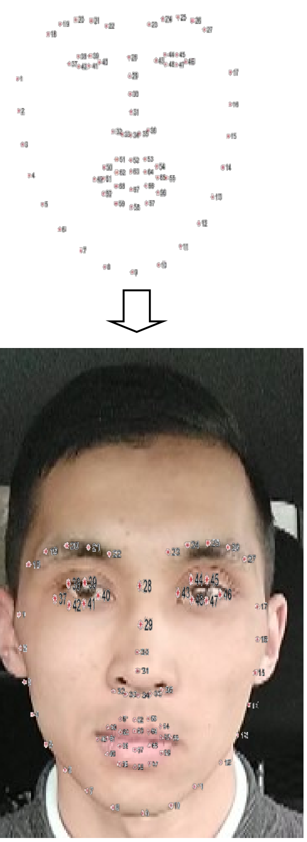

Figure 8: Visualization of facial features

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In order to check if the driver in the video stream is starting to show symptoms of drowsiness, first determine if the aspect ratio of the eye is below the “blink / closed” threshold. If so, then the counter is incremented, the total number of consecutive frames in which the driver's eyes were closed. If the counter value exceeds the set maximum number of frames, then it can be assumed that the driver is starting to fall asleep.

Figure 9: The driver is starting to fall asleep

Next, another check is made to see if the beeper is enabled – if not, it is enabled. Then, the playback of the audio signal is processed. Finally, the case where the aspect ratio of the eye is greater than the threshold value is handled, indicating that the eyes are open. If the eyes are open, the counter is reset and the audio notification is not played.

4. ACKNOWLEDGMENTS AND FURTHER RESEARCH

Part of the research was carried out with the support of the “Sustainable Mobility Research in Central Asia (SUMRICA) project” and Technische Universität Berlin.

Further research will consider the treatment of some additional symptoms of driver drowsiness. There are studies that show that it is not enough to focus only on the state of the eyes and the position of the body, for example [54].

Symptoms of driver drowsiness:
- has difficulty focusing vision;
- blinks frequently;
- feels that the eyelids are heavy;
- it is difficult to keep the head straight;
- often yawns;
- drives past road signs without paying attention to them;
- often moves out of his lane;
- it is difficult to keep a distance;
- touches the noise strip on the side of the road.

The words “fatigue” or “drowsiness” are used to describe the totality of factors leading to a violation of professional activity. Fatigue in this case is considered as a hypothetical concept that links a number of factors that cause the development of fatigue, causing a violation of the safety of drivers. The development of fatigue is connected with three main indicators:

1) insufficient sleep duration, taking into account the duration of the previous ratio of wakefulness and sleep;

2) time of day (circadian rhythm);

3) the nature of the work (duration, intensity, complexity).

The main reason for the violation of any professional activity is drowsiness. The transition to a state of drowsiness occurs slowly, gradually weakening the ability of the driver to fully control the vehicle. Drowsiness interferes with vigilance and attention on the track, which can be the cause of an emergency. Although the causes of fatigue and drowsiness may be different, their outcome is the same - a decrease in mental and physical performance.

It is also planned to take into account additional difficulties with the processing of the video sequence, such as the presence of glasses for the driver, headgear, etc.

Figure 10: The driver with glasses

5. CONCLUSION

The main objectives of the work were achieved.

1. It was done analysis of existing technologies, devices and active safety systems for the driver of a vehicle, focused on early warning and prevention of traffic accidents, as well as existing methods and algorithms for intelligent analysis of video surveillance data.

Today, more and more professions require concentration in the long run. Drivers must pay close attention to traffic in order to respond quickly to unexpected situations. Driver fatigue is usually the immediate cause of several traffic accidents. It is given the analysis of existing technologies, devices and systems of active safety of the driver, focused on early warning and prevention of traffic accidents. Approaches are presented to the development of such systems, divided into four main classes, including modern driver assistance systems, mobile recommendation generation systems, internal video surveillance cameras and wearable electronics devices. Opportunities, advantages and disadvantages, limitations of each class of active safety systems are given. On the basis of the features of the construction of existing solutions, the requirements for the construction of a separate class of systems, a distributed system for preventing emergency situations, are formulated.

2. As a new method the two classifiers were used for simulation and algorithms' development for improving driver real time safety.

It was used dynamic learning process (on-line learning) in order to increase in detection efficiency, since over time the algorithm makes fewer errors on new objects. After detecting the next object, the algorithm is given the class label of this object, which it must take into account, i.e., "learn more".

Since the Viola-Jones classifier does not support retraining, it is necessary to use a second classifier that is not inferior in quality to the Viola-Jones method and can support online learning. Such a classifier is the support vector machine.

3. It was developed an automated video tracking system using the proposed methods.

Thus, an application has been developed that is capable of detecting driver drowsiness and alerting them to a dangerous condition.

The drowsiness detector can operate in a variety of environments, including direct sunlight while driving on the road and low or artificial lighting. At the moment, the developed application has several limitations. Most significant is the inability to detect eyes in low light. Most drowsiness occurs at night, and the effectiveness of the program in the dark is reduced. Another limitation is the time delay between the count during which the eyes were closed and the alarm. By using better equipment, the overall efficiency of the system can be improved.

The reliability of the results obtained is confirmed by a deep analysis of research and approaches to the development of active safety systems, correct substantiation of problem statements, precise formulation of the principles of system construction, as well as successful testing of the results at international conferences.

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