Image-Based Fatigue Detection of Vehicle Driver: State-of-the-Art and Reference Model

Alexandr Bulygin, Alexey Kashevnik
St. Petersburg Federal Research Center of the Russian Academy of Sciences (SPC RAS)
Saint Petersburg, Russia
alexandr_bulygin@mail.ru, alexey.kashevnik@iias.spb.su

***Abstract*—The paper analyzes modern methods of driver fatigue detection. There are a huge variety of methods for assessing the functional states of a person. The detection of the dynamic behavior of the driver in recent years has become an increasingly popular area of research. Dynamic assessment of driver behavior includes long-term monitoring, which allows determining functional states, in contrast to modern driver monitoring systems, which assess conditions such as drowsiness and impaired attention for a short (1-10seconds) time interval. Such systems allow us to talk about physiological monitoring, but not neurophysiological, which allows monitoring the functional state of fatigue. Therefore, it makes sense to monitor the state of fatigue of the driver, as well as to warn him in a timely manner in order to avoid collisions with other vehicles.**

I. Introduction

Methods of analyzing driver fatigue have become an increasingly popular research area in recent years. Such methods include long-term monitoring, which allows to determine the functional states.

Driving in a state of fatigue is one of the main causes of road accidents. Studies show that the probability of road accidents caused by driving in a state of fatigue is five times higher than when driving in a normal state. Annual road traffic accidents caused by driving in a state of fatigue account for about 20 % of the total number of accidents and more than 40% of serious road accidents [1].

Drowsiness is a property of a person in which the eyelids are lowered below their normal state, yawning, nodding of the head appears, the time of opening and closing the eyes increases, and the frequency of blinking increases [2]. Falling asleep is a state of drowsiness, a decrease in brain activity, characterized by a decrease in the level of consciousness, yawning, a decrease in the sensitivity of sensory systems, a decrease in heart rate, a decrease in the secretory activity of the glands [3].

Sleep is a normal, reversible, repetitive state of reduced sensitivity to external stimulation, which is accompanied by complex and predictable changes in physiology. These changes include brain activity, as well as fluctuations in hormone levels and muscle relaxation [4].

Fatigue is a temporary decrease in performance under the influence of prolonged exposure to stress. It occurs due to the depletion of the individual's internal resources and the mismatch in the work of the systems that support the activity. Fatigue has various manifestations at behavioral (reduced labor productivity, reduced speed and accuracy of work), physiological (difficulty in developing conditional connections, increased inertia in the dynamics of nervous processes), psychological (decreased sensitivity, impaired attention, memory, intellectual processes, shifts in the emotional and motivational sphere) levels. It is accompanied by the formation of a complex of subjective experiences of fatigue. The specificity of fatigue manifestations depends on the type of load, the localization of its impact, the time required to restore the optimal level of performance [5].

Computer vision methods are used to monitor the functional state of the driver in the cab of the vehicle. These methods are not intrusive and do not cause inconvenience to the driver while driving a vehicle, and also do not require additional special equipment.

Neural networks can also be used to detect the driver's fatigue at the wheel. There are a large number of datasets of drivers driving on the Internet in open access. These datasets can be used for training neural networks.

Thus, tracking the state of driver fatigue is an important scientific and technical task that will allow you to warn the driver in order to avoid collisions with other vehicles. In the paper we analyze state-of-the-art in the topic of fatigue detection and propose the reference model where we have summarized the analyzed approaches.

The structure of the paper is as follows. In Section II we present the state-of-the-art in the topic of fatigue detection techniques. Section III describer the reference model that is based on the considered related work analysis. Conclusion summarizes the paper.

II. State-of-the-Art

A. Driver Monitoring

The section discusses considered papers on methods for determining the position of the head, the percentage of time when the eyes are closed (PERCLOS), the speed of blinking of the eyelids, the direction of gaze, yawning, respiratory rate, skin temperature (ST). These methods are most often used to monitor the driver's behavior.

Eye recognition is necessary to monitor the driver's behavior, determine drowsiness, inattention, and fatigue. A distinctive parameter of PERCLOS is the closing time of the eyelids by more than 80 %. If the PERCLOS indicator is observed for more than 28 % of the time within one minute, then the state of drowsiness is recorded [6]. In the paper by drowsiness the author understands the feeling of "eyes sticking together". The state of drowsiness is characterized by a longer and slower blinking of the eyes, the frequency of blinking may change, the eyelids may fall with a small amplitude. There may be states of short-term "micro-sleep". These are situations in which the eyes are closed for 3-5 seconds or more.

The time interval from 0.5 to 0.8 seconds is considered safe when the driver is blinking. If the driver "nods his nose", then this also creates a dangerous situation. It is difficult for him to keep his head in the usual position.

By searching and tracking the driver's face, the system identifies dangerous situations of drowsiness, inattention, and a functional state of fatigue. A developed mobile application is installed on the smartphone, which uses the front camera and sensors (GPS, accelerometer, gyroscope, magnetometer) to obtain an image and monitor the functional state of the driver.

The paper [7] presents a hybrid visual system for tracking the states of drowsiness, inattention, and fatigue of the driver based on eye recognition. The operation of the system is implemented in a vehicle and image processing in daytime and night light conditions is achieved thanks to the individual configuration of two cameras operating in the visible and near-infrared spectra, respectively. Both processing options are organized in the form of a cascade of specialized modules. The second module receives as an input the result of the previous module. Such connections of many classifiers are usually characterized by higher accuracy. A morphological filter is applied to the image to remove spots from the iris and noise. Then the eye detection is performed based on the proposed eye model. First, the pupils are determined, then the iris, and then the eye areas. The second classifier determines the openness of the eyes in the image. This classifier is based on the decomposition of HOSVD tensors, so it is called a HOSVD classifier. This module is preceded by the Euclidean transformation, the role of which is to create an image that takes into account the mutual relations of pixel positions. The HOSVD classifier is trained using images with eyes and images without eyes. Both processing paths use the same type of HOSVD classifier trained with different sets of templates. Depending on the degree of eye openness and the frequency of blinking, the system determines the degree of fatigue of the driver.

In the paper [8] the aim of the work is to develop an algorithm for monitoring the head and eyes to determine the drowsiness and fatigue of the driver. The Viola-Jones algorithm is used for face recognition. This algorithm allows to detect objects in images in real time. The standard Viola-Jones algorithm uses rectangular Haar features. The simplest rectangular Haar feature can be defined as the difference between the sums of pixels of two adjacent areas inside a rectangle that can occupy different positions and scales in the image.

When assessing the frequency of eye blinking, all three parameters are taken into account: spontaneity, reflexivity, arbitrariness, and on their basis, signs that determine the driver's state of drowsiness are recognized.

The JEER method is used to determine the eye area to monitor the frequency of blinking. The procedure is divided into 2 stages. First, the eyes are searched and it is assumed that the tip of the nose is located between them. Then the forehead is determined in the image. By summing up the pixel values in the areas where the eyes are located, it is determined whether the eyes can be located in the areas selected in the previous step. If the sum of the pixel values in the area of each eye is the same, then it is assumed that the algorithm has determined the eyes correctly.

In the paper [9] a fuzzy expert system classifies the driver's fatigue levels into low, normal, and high. A fuzzy expert system is an expert system that uses fuzzy logic instead of Boolean logic. The face recognition algorithm for all frames is computationally complex, so when a face is detected in the first frame, then the face tracking algorithm is used.

For face recognition, Haar signs and the Viola-Jones algorithm were used. The facial recognition algorithm was trained on 3,000 images with faces and 300,000 images without faces. There are two types of features in this system. Signs received from the eye area, and signs received from the head as a whole. The signs obtained from the eye area include the values of PERCLOS, the change in the distance between the eyelids (ELDC) and the rate of closing of the eyes (CLOSNO). A feature related to the head area is the rotation of the head (ROT). The rotation of the head is a sign of distraction. The rotation of the head is estimated based on changes in the image of the face in relation to the template of the frontal face. The driver's head and face were obtained from the image using pattern matching and a horizontal projection of the face image. Then these signs (PERCLOS, ELDC, CLOSNO, ROT) are input to the fuzzy expert system. The output of the fuzzy expert system is the level of driver fatigue.

This method was tested on five subjects in real driving conditions. Determination of fatigue is performed using an electroencephalogram (EEG) as an objective assessment of fatigue. The face tracking method is inaccurate, very complex from the point of view of calculations, and the accuracy is significantly reduced in low light conditions.

In the article [10] a fatigue detection system was developed specifically for bus drivers using a dome camera already installed in buses to monitor driving behavior.

The eye openness is assessed and the PERCLOS method is used as a method for detecting driver fatigue. The head-shoulder detector is used to detect the presence of a driver behind the wheel and determine the approximate position of the head. The head and shoulders are determined using a directed gradient histogram (HOG), and the driver is detected using the Support Vector Machine (SVM). Face and eye detection are performed by the OpenCV face detector and the eye detector, respectively. The OpenCV face detector is reliable for searching for frontal faces since it is trained on a large number of examples. The OpenCV eye detector works well to determine the location of the eyes on images of frontal faces, even with the eyes closed. Eye openness is calculated using linear and spectral regression. The method of assessing the openness of the eyes is used, based on the full image of the eye so that there is no need to detect characteristic points and curves around the eyes. In order to accurately determine the driver's fatigue based on eye images, eye openness is measured continuously. The fuzzy logic system then determines the driver's fatigue based on the detected eye characteristics. The authors conducted testing on 23 drivers in real driving conditions. This system has limited computing resources and works with images of faces and eyes observed at an oblique viewing angle. Therefore, fatigue detection works for low-resolution images and the method is designed for a dome camera installed in buses.

B. *Psychophysiological Parameters Estimation*

The paper [11] says that by determining the driver's facial expression, the openness of the eyes and mouth, calculating the frequency of blinking, and the frequency of yawning, it is possible to determine the state of fatigue of the driver. The authors consider an algorithm for determining fatigue based on the analysis of facial expressions. The model of the position of the eyes and mouth is trained using multi-block local binary templates MB-LBP. The positions of the eyes and mouth in the image of the driver's face are determined, and the PERCLOS and the frequency of yawning are calculated to describe the driver's fatigue.

The eyes and mouth can be in one of three states: closed, half-open, and fully open. The state of fatigue is also divided into three levels: normal, mild fatigue, and severe fatigue.

There is no special database on driver fatigue, so the experimental data in this article are obtained from 400 laboratories that simulated driving conditions (normal condition, mild fatigue, severe fatigue).

By testing the frequency of blinking and yawning from normal to mild fatigue and severe fatigue under different lighting conditions, the PERCLOS values corresponding to different states of fatigue are analyzed. The three state thresholds for eye PERCLOS (P) and mouth PERCLOS (K) are shown in Table I.

The authors of the study obtained three states of the frequency of eye blinking and the frequency of yawning: low-frequency, intermediate, high-frequency. Then we created Table II, where the frequency of blinking and yawning corresponds to the state of fatigue with the values: normal state, slight fatigue, and severe fatigue.

The paper [11] uses psychophysiological signals and task performance indicators to assess the functional state (FS) of fatigue at various levels of mental load. Three indicators were extracted from the electrocardiogram (ECG) and electroencephalogram, including heart rate (HR), heart rate variability (HRV) - the ratio of the standard deviation to the average value of the heart rate segment, task load indices (TLI1 and TLI2), are selected as input data of the proposed model. Heart rate and heart rate variability are effective indicators of mental load. To evaluate the FS, the task load index is selected. In this study, HR, HRV, and TLI were selected as input data for the proposed FS assessment model. The experiments were carried out on an automated cabin air control system (AUTOCAMS). AUTOCAMS simulates the spacecraft's life support system. The subject must operate a semi-automatic system that must regulate the atmospheric conditions of the cabin in such a way as to maintain a comfortable atmospheric pressure.

The primary task of the subject was to control some of the five subsystems in order to maintain their respective variables in the target ranges. The number of subsystems that must be manually controlled under each control condition is 1, 2, 3, 4, 5, 4, 3, 2 and 1, respectively. Thus, during the experiment, the load required to complete the task changes. At the end of each control state, the subjective state of anxiety, effort, and fatigue was measured using the NASA Task Load Index (NASA-TLX) on-screen visual analog scales. This scale allows you to assess the mental load over a long period of time.

The paper [13] proposes a model for assessing the functional state of human fatigue, which is trained on ECG, EEG, and heart rate variability signals obtained using near-infrared functional spectroscopy (fNIRS).

TABLE I. PERCLOS-THRESHOLDS FOR THE EYES AND MOUTH

Condition	**Low-frequency**	**Intermediate**	**High-frequency**
eyes	$P<13\%$	$13\%<P<21\%$	$P>21\%$
mouth	$K<20\%$	$20\%<K<30\%$	$K>30\%$

TABLE II. MATCHING THE FREQUENCY OF BLINKING AND YAWNING TO THE STATE OF FATIGUE

Situation	Eyes	Mouth	Result
1	low	low	normal condition
2	medium	low	slight fatigue
3	high	low	severe fatigue
4	low	medium	normal condition
5	medium	medium	severe fatigue
6	high	medium	severe fatigue
7	low	high	slight fatigue
8	medium	high	severe fatigue
9	high	high	severe fatigue

fNIRS is used for functional neuroimaging. This method of examination is more accessible than magnetic resonance imaging (MRI) and has no restrictions on the environment of use. It has been shown that fatigue can be assessed using physiological information obtained from the brain using an electroencephalogram and functional near-infrared spectroscopy. Another physiological information that is commonly referred to as a stress marker is heart rate variability. This is a measure of changes in the time intervals between heartbeats controlled by the autonomic nervous system. This indicator was used to assess fatigue both individually and in combination with measurements of the galvanic reaction of the skin, skin temperature, blood pressure, and EEG.

In the paper [14], a system for monitoring driver fatigue and drowsiness is proposed, in which a built-in ECG sensor attached to the steering wheel is used to measure ECG signals from the driver. A pair of conductive fabric electrodes are wrapped around the steering wheel of the car, and both electrodes are connected to the built-in ECG sensor. The proposed system consists of three parts: pairs of conductive electrodes located on the steering wheel with a built-in ECG sensor, a wireless sensor node and a server for signal processing and monitoring. The ECG signals measured by the conducting electrodes are transmitted to the base station, which is connected to the server.

Analysis of changes in heart rate in the time and frequency regions of ECG signals provides valuable information about the driver's condition, including the state of normality, drowsiness and fatigue. Thus, an increase in heart rate variability indicates the onset of fatigue. One of the existing non-intrusive methods of measuring the ECG signal is the measurement of the inductance on the driver's seat. The ECG signal can be measured using electrodes on the back of the driver's seat. However, this method of ECG measurement is very sensitive to the thickness of the driver's clothing. In order to overcome these limitations, pairs of electrodes made of conductive tissue are located on the steering wheel to measure ECG signals.

This method of determining fatigue is not intrusive and does not cause inconvenience. This is an important quality for a person while driving a car.

In the paper [15], driver fatigue is estimated based on bursts of alpha rhythms of electroencephalography. The EEG was obtained from the participants of the experiment in a monotonous driving environment.

During the experiment, the subject had to drive the track on a simulator of a car cab in daytime conditions (task_0). Based on the data obtained, the base time of the route passage is in a normal functional state. In the second task, it was necessary to reduce the time of passing the route by 2% (task_1). The requirements of the third task (task_2) were similar to the requirements of task_1, but other road users appeared on the highway, traffic lights, traffic jams formed. The fourth (task _3) and fifth (task_4) tasks were equal to task_1 and task_2, respectively, but at night. When performing task_4, the condition was added that the subject had to drive very carefully, not exceeding the speed of 70 (km/h). In the future, the fatigue characteristics were determined from the data of the peaks of the alpha rhythms of the EEG, defined as short flashes in the alpha range.

The subjects performance of the first four tasks did not cause noticeable spikes in the alpha rhythm and the number of driving errors was minimal. When performing the fifth task, the subjects began to make much more mistakes, and there were spikes in the alpha rhythm, which indicates the onset of fatigue.

Fig. 1 shows an example of the appearance of such bursts in the alpha rhythm of the EEG (circled in red) that occur during monotonous driving (task_4) as a fatigue signal. After the appearance of such specific EEG indicators, the subjects moved off the correct trajectory of movement, made mistakes when driving. The main frequency of such EEG peaks was noted in the subjects over the central parietal region of the head.

It was concluded that the bursts of the alpha range of the EEG increase with fatigue. The results show how neurophysiological signals can help in assessing the fatigue, as well as the mental and physical condition of the driver in various driving conditions and how they correlate with driving efficiency.

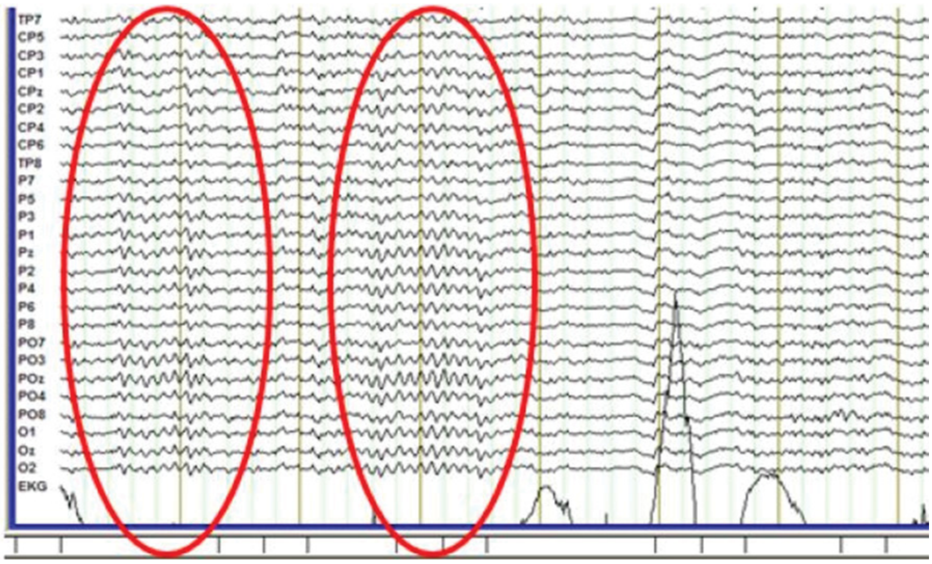

Fig. 1. Bursts of alpha rhythm that occur during fatigue

C. Datasets

In the paper [16] presents the dataset for detection of the yawning of drivers. A dataset of videos, recorded by an in-car camera, of drivers in an actual car with various facial characteristics (male and female, with and without glasses/sunglasses, different ethnicities) talking, singing, being silent, and yawning. In the video, the driver's face and mouth are highlighted with rectangles. The videos are taken in natural and varying illumination conditions. The videos come in two sets. In the first set, the camera is installed under the front mirror of the car. This set provides 322 videos, each for a different situation: 1- normal driving (no talking), 2- talking or singing while driving, and 3- yawning while driving. Each subject has 3 or 4 videos. In the second set, the camera is installed on the driver's dash. This set provides 29 videos, one for each subject, and each video containing all of driving silently, driving while talking, and driving while yawning.

In the paper [17] presents the DMD dataset. The dataset contains 40 hours of video recordings of 37 drivers driving a car. 27% were women and 73% were men. The average age of the participants is 30 years (all over 18 years old). 10 of the participants wore glasses, some were recorded with and without wearing them. The recordings present variation in lightning angle conditions according to the time the session was recorded (morning or afternoon). All recordings were grouped by sessions, each one determined by a protocol of activities, a participant, an environment, and a lighting condition. In each session, there were 3 cameras recording simultaneously the face, body, and hands. Each camera captures 3 channels of information: RBG, infrared, and depth.

In the paper [18] presents the Drive&Act dataset. Dataset features twelve hours and over 9.6 million frames of people engaged in distractive activities during both, manual and automated driving. The dataset contains color, infrared, depth, and 3D body pose information from six views. Challenges of the dataset are recognition of fine-grained behavior inside the vehicle cabin; multi-modal activity recognition, focusing on diverse data streams; and a cross-view recognition benchmark, where a model handles data from an unfamiliar domain, as sensor type and placement in the cabin can change between vehicles.

In the paper [19] presents the RobeSafe Driver Monitoring Video Dataset (RS-DMV). The RS-DMV dataset is a set of video sequences of drivers, recorded with cameras installed over the dashboard. The dataset contains 10 video sequences. The drivers were fully awake, talked frequently, and were asked to look regularly to rear-view mirrors and operate the car sound system. Sequences contain occlusions, illumination changes, and other elements that are problematic to face tracking and driver monitoring systems using computer vision.

Frames are recorded in gray-scale, at 30 frames per second, and stored as RAW video. The frame size of outdoor videos is 960x480 pixels, and 1390x480 for indoor videos. Faces in the videos have been marked with 20 points.

In the paper [20] presents the State Farm dataset. The StateFarm dataset contains snapshots from a video captured by a camera mounted in the car. The training set has ~22.4 K labeled samples with equal distribution among the classes and 79.7 K unlabeled test samples. There are 10 classes of images: safe driving, texting-right, talking in the phone – right, texting – left, talking on the phone – left, operating the radio, drinking, reaching behind, hair and makeup, talking to passengers.

III. Reference Model

This paragraph consists of methods that use intrusive sensors attached to the driver. Electrocardiogram data contains information about heart rate variability. HRV is a measure of changes in the time intervals between heartbeats controlled by the autonomic nervous system. If the standard deviation of the intervals of instantaneous heart rate values (NN) SDNN < 141 +/- 39 ms [21], then fatigue is detected. The HRV signal can be received using a heart rate monitor attached to the wrist (Fig. 2). Muscle fatigue can be assessed using electromyography (EMG).

EMG sensors register the electrical potential generated by muscle cells through electrodes (Fig. 3). The characteristics extracted from the EMG time and frequency domain signal can be used to predict muscle fatigue. Studies show that there is a link between EMG amplitude and muscle fatigue since the amplitude of EMG signals gradually decreases with fatigue. There is also a correlation between muscle fatigue and drowsiness. With an increase in muscle fatigue, drowsiness increases. If the peak coefficient of the EMG signal Fc (1) is greater than 0.15, then fatigue is detected in a person.

$$F_c = \frac{A}{x_{rms}}, \quad (1)$$

where A is the EMG amplitude, and xrms is the square root of the EMG.

Let's consider the approaches that use intrusive methods and image processing methods. The driver-looking direction can be estimated using image processing methods. If the gaze is directed down, then drowsiness and loss of concentration are detected. Also, the direction of the driver's gaze can be estimated using electrooculography (EOG).

Fig. 2. Bursts of alpha rhythm that occur during fatigue

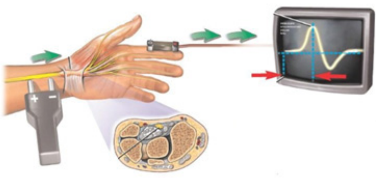

Fig. 3. Example of attaching electrodes to a person

EOG is a measurement of the retinal potential difference between the back and front parts of the eye. The EOG measures the movement of the eye using electrodes attached to the left and right sides of the eye. When using EOG, if the voltage U>50 μV, then the driver experiences drowsiness. Electroencephalography can be evaluated using near-infrared functional spectroscopy. The fNIRS method is non-intrusive. When using this method, if the value of oxygenated hemoglobin HbO2 is greater than 2, then the subject experiences fatigue. Also, the dynamic parameters of the EEG are bursts in the alpha rhythm of the EEG. If the frequency of the alpha rhythm μ_α = 7-9 (Hz), then a person has a state of fatigue.

The following fatigue assessment methods use image processing methods. Eye openness is used to evaluate three dynamic parameters. If the blinking frequency μ_β is greater than 13 times/min then drowsiness is detected. If PERCLOS is greater than 28%, then it is considered that the subject has drowsiness. An indicator such as ELDC (2) is also used.

$$ELDC = 1 - Sigm(Corr(HP_O, HP_{LO}), \propto_S, \beta_S) \quad (2)$$

If the ELDC is close to zero, the distance between the eyelids is normal, but if the ELDC is approaching one, the distance between the eyelids is approaching zero (the eye is closed). Thus, if ELDC is greater than 0,5, then the state of drowsiness is determined. Methods of measuring skin temperature t using an infrared camera measure the temperature of the skin surface, which varies depending on the level of drowsiness. When the skin temperature drops by 0,1 °C, drowsiness is detected. The respiratory rate T_{br} is the number of exhalations and breaths per one minute. The respiratory rate is measured using a camera. The respiratory rate begins to fall with the onset of drowsiness and continues to fall until the onset of sleep. If the T_{br} is less than 16 times/min [11], then it is considered that the person is in a state of drowsiness. By calculating the time of yawning T_y, you can determine the state of fatigue of the driver. There is no special database on driver fatigue, so the experimental data in this article are obtained from 400 laboratories. By testing the frequency of blinking and yawning from normal to mild fatigue and severe fatigue under different lighting conditions, the PERCLOS values corresponding to different states of fatigue are analyzed. If the yawning time is more than 30% within a minute, then a state of fatigue is recorded [11]. The angles of rotation A_y and tilt A_p of the head are used to determine the loss of concentration. If A_P is greater than 10 or Ay is greater than 25 [11] the driver's concentration loss is detected.

Self-analysis methods include the NASA Task Load Index [13] which evaluates the perceived workload to assess the effectiveness of a task, system or team, or other aspects of work. In this method, the subjects themselves determine their level of fatigue. As a result, a corresponding scheme of fatigue analysis methods was obtained, presented in Fig. 4.

IV. Conclusion

Methods that process biological signals that can be used in laboratories and car simulators include such methods as electroencephalography, electrocardiogram, heart rate variability, respiratory rate, electrooculography, electromyogram (EMG), galvanic skin reaction (GSR), electrothermal activity (ETA), skin temperature, NASA-TLX analog scale, near-infrared spectroscopy. The activity of the autonomic nervous system (ANS) changes due to stress or fatigue. HRV decreases with the onset of fatigue. The respiratory rate begins to fall with the onset of drowsiness and continues to fall until the onset of sleep. An increased frequency of blinking is an indicator of drowsiness. With an increase in muscle fatigue, drowsiness increases. With a decrease in sweating, drowsiness increases. The temperature of the forehead skin decreases significantly with the onset of drowsiness. The appearance of bursts in the alpha rhythm of the EEG indicates the onset of fatigue.

In real driving conditions, the detection of the functional state of fatigue can be carried out on the basis of the use of modern computer vision technologies to assess physical characteristics. Physical features include the opening/closing of the eyes, the frequency of blinking, the frequency of yawning, the duration of eye closure, PERCLOS, the position of the head, the direction of gaze, nodding of the head, ELDC, CLOSNO, ROT.

To determine fatigue in the car, systems were developed using such methods as multi-block local binary patterns MB-LBP, Haar signs, the Viola-Jones algorithm, the JEER method, fuzzy logic, the support vector machine (SVM) method. The paper presents a table of the correspondence of the frequency of blinking and yawning to the state of fatigue with the values: normal state, slight fatigue, and severe fatigue.

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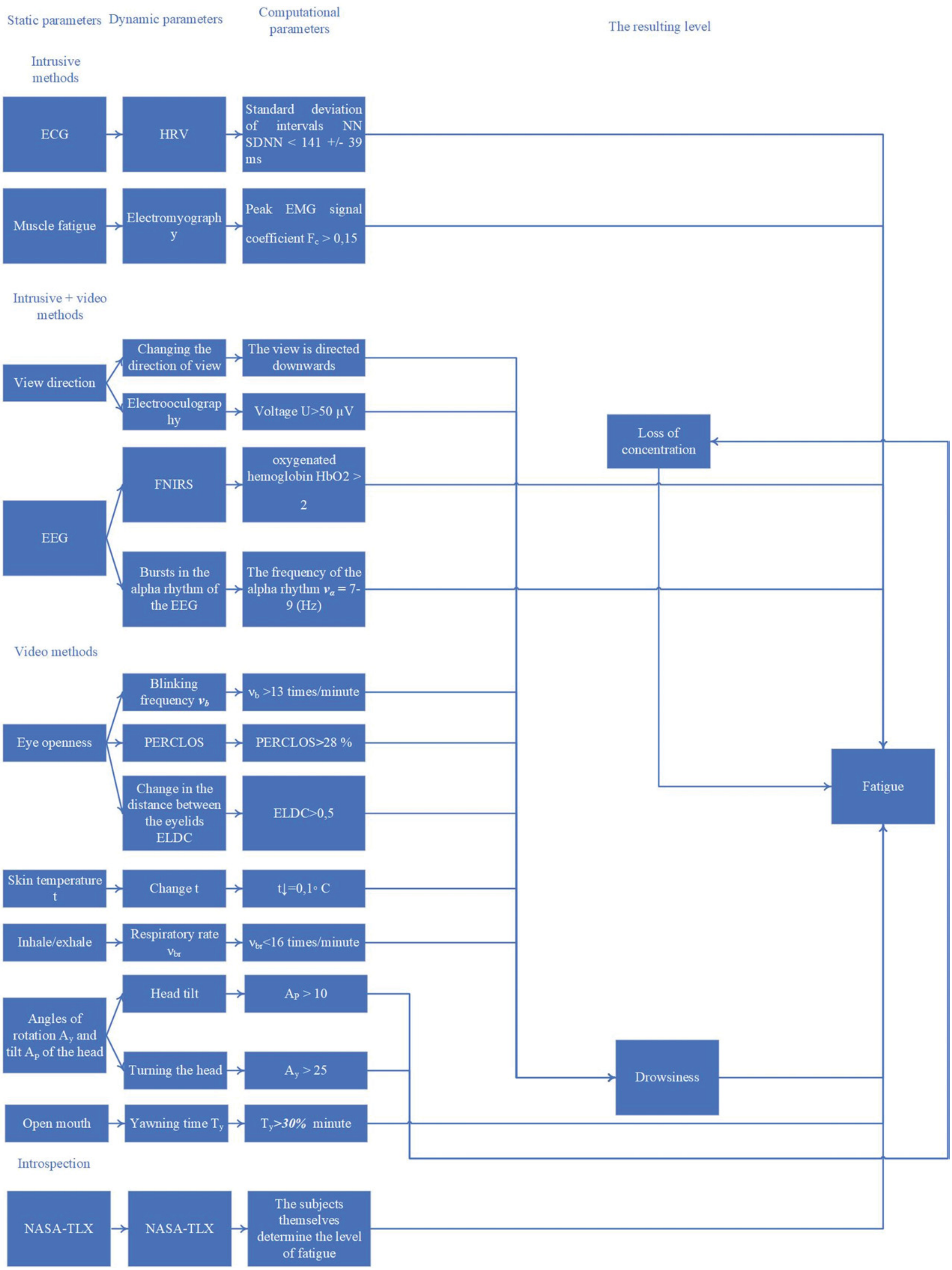

Fig. 4. Fatigue analysis methods