Algorithm For Dynamic Fatigue Detection of PC Operator Based on Gaze Characteristics

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The onset of fatigue is dangerous in areas of activity that require high concentration of human attention, such as air traffic controllers, nuclear power plant operators, etc. It should be noted that these types of activities are characterized by the fact that most of the time the employee sits at the workplace and his gaze is directed at the monitor. The paper presents the algorithm for dynamic fatigue detection of PC operator based on eye movement characteristics. The algorithm for dynamic fatigue detection includes preparation stage and fatigue detection stage. Within the preparation stage, gaze movement characteristics are calculated and correlations with fatigue test results are searched for. Within the fatigue detection stage, eye movement characteristics that most strongly correlate with fatigue are selected. These characteristics can also be divided by the types of physical events on which they are based. We can distinguish such characteristics as speed, percentage, saccade length, curvature of gaze trajectory. To find correlations between eye movement characteristics and fatigue, a dataset of eye movements and the results of tests and questionnaires such as the go/no-go task, the "Landolt rings" test, and the VAS-F questionnaire were analyzed. The dataset consists of gaze coordinate recordings from 15 participants acting as PC operators. To assess the degree of fatigue, the participant completed the VAS-F questionnaire. The "Landolt rings" test is a test used to measure attention concentration. The labeled dataset is used to train a machine learning model that detects fatigue. The experimental results showed that using the characteristics selected in the study yielded the most promising results. This approach allowed us to achieve the highest F-score and the best average accuracy, indicating the overall reliability of the model.

I. INTRODUCTION

Reduced performance due to fatigue is accompanied by loss of attention and slower reaction time, and an increase in the number of errors. Such errors often lead to catastrophic consequences in the work of representatives of various professions: air traffic controllers, nuclear power plant operators, ship, airplane, train, freight, public and personal vehicle drivers. Rapid detection of fatigue symptoms is the main principle of preventing negative consequences. Nuclear power plant operators work in teams in a large control room, where hundreds of devices, screens and indicators are located. The air traffic controller's workplace is located in a tower located next to the airport building. The air traffic controller workplaces inside the tower are arranged in a circle and are tables with monitors on them. The profession of a PC operator is mainly associated with working on a computer. A PC operator is engaged in typing, processing information, compiling tables, formatting documents, etc. Thus, these professions are similar in that the worker sits at his workplace and his gaze is directed at the monitor. Therefore, a unified fatigue detection algorithm for these types of activities can be developed.

Eye movement characteristics provide insight into cognitive processes such as decision making and attention concentration. Eye movement characteristics such as saccades, blinks, and fixations engage different neural circuits involved in visual motor processing. It has been suggested that peak saccade velocity, saccade duration, fixation duration, blink duration, blink rate, and pupil dilation range may be sensitive to changes in mental workload and fatigue [1]. For example, peak saccade velocity, saccade duration, fixation duration, blink duration, blink rate, and pupil diameter may reflect changes in fatigue [2].

In this work, a dataset consisting of the oculomotor activity of PC operators and the corresponding go/no-go task and psychological questionnaires of his state was used. As a result of the experiment, the following operator parameters were recorded: oculomotor activity, go/no-go task, and psychological questionnaires of his condition. The developed algorithm for dynamic detection of PC operator fatigue consists of a preparation stage and a fatigue detection stage. The preparation stage is designed to train the machine learning model. The result of the fatigue detection stage is a detection of PC operator fatigue.

First, such gaze movement characteristics as speed, time, proportion of characteristics from the total number, quantitative, saccade length characteristics, and gaze movement trajectory curvature characteristics are calculated. Fatigue is detected based on such tests as go/no-go task, the "Landolt rings" test, and the VAS-F fatigue questionnaire. Then, a search is made for correlations between eye movement characteristics and fatigue assessments based on tests. Further, based on the correlations, experts select characteristics for training the machine learning model. The trained model uses the architecture of the machine learning model, which contains such classifiers as random forest, decision tree, and multilayer perceptron. And finally, using the trained model, the computer detects fatigue. This algorithm also differs in detecting the characteristics of eye movements that most accurately correlate with the reference values of operator fatigue.

The structure of the paper is as follows. In Section II we present the review of existing algorithms of fatigue detection. Section III describes the eye movement dataset that is used for calculation of eye movement characteristics and training of the machine learning model. Section IV describes the algorithm for dynamic detection of PC operator fatigue. Section V describes the results of experiments and such indicators like F-score and accuracy. Conclusion summarizes the paper.

II. REVIEW OF EXISTING ALGORITHMS OF FATIGUE DETECTION

Eye movements can indicate the onset of drowsiness and fatigue. The characteristics of eye movements are calculated from such basic concepts as fixation and saccade. Saccades are rapid eye movements that usually occur when reorienting the gaze to a new target. The speed of eye movement often exceeds 500 deg/s, the average duration is from 20 to 40 ms [2]. Fixations correspond to time intervals when the subject looks at a certain point, usually at the object of interest. Their duration usually ranges from 200 to 500 ms, with an average of about 300 ms [2].

One method of fatigue detection using oculomotor movements is based on the analysis of peak pupil acceleration values. In [3], these parameters were studied by comparing tired and energetic taxi drivers. The number of peak values in tired drivers was 62% higher than in energetic ones. In order to make their algorithm suitable for real-time signal processing, the authors used a z-score, which allows adaptive detection of peak values. With this score, the calculation of peak values is more accurate; the difference between their number in a tired and energetic driver is more than two times. An energetic person makes more eye movements compared to a tired person in the same test environment.

Peak saccade velocity is an indicator that decreases due to an increase in fatigue. In the work [4] about fatigue detection, participants were placed in a virtual environment simulating driving a car for 2 hours. Before and after the driving session, as well as after a short break, the participants underwent a controlled fixation test. As a result of the saccade analysis, the authors revealed an increase in duration and a decrease in peak velocity. In addition, they found that a 15-minute break after the stress task is insufficient for the body to recover and return to the initial level of fatigue. It was concluded that the degree of fatigue and the decrease in saccade velocity, in addition to the complexity of the task, are affected by its duration [5]. To test this hypothesis, the authors conducted an experiment, testing surgeons before and after a 45-minute operation. Participants were required to focus on target symbols in different parts of the screen [6]. A decrease in the maximum saccade velocity in relation to its length is described in the work [7] on the detection of fatigue during flight. The value of this indicator decreased by 3%. A decrease in the average and peak saccade velocities has been well studied under sleep deprivation conditions [8].

In the work [9], the maximum velocity and length of saccades were measured during the go/no-go task. As a result, it turned out that the values of the maximum speed decrease, and the amplitudes increase, which does not correspond to the results of the work [10]. This may be due to different approaches to measuring the saccade amplitude. In the work [11], the authors note a decrease in the response speed compared to an increase in the value of the peak saccade speed, and in addition, the reaction time decreases as mental fatigue increases.

In the work [12], two experiments were conducted using the following types of tasks: a gaze-controlled saccade task and an antisaccade task using emotional auditory stimuli. To detect fatigue, the speed characteristics of saccades were used. After analyzing the data, the following results were obtained: during the execution of the time on task (TOT), the maximum saccade speed decreased, since this parameter is sensitive to the level of excitation.

Such parameters as the frequency and duration of blinks often appear in the study of the relationship between oculomotor events and fatigue. In the work [13], it is stated that many studies reflect how the values of these parameters increase with fatigue.

The work [14] describes changes in neurophysiological indicators for assessing mental workload and fatigue. There is a decrease in the duration and frequency of blinks with increasing task complexity. This is due to the fact that a complex task requires more attention and leads to a decrease in the time with eyes closed. In [15], a study of fatigue in young and elderly people is presented. The following results were obtained: the frequency and duration of blinks increased when performing TOT. The change in blink frequency is associated with a change in the level of attention. When studying three types of fixation duration (<150 ms, 150–900 ms, >900 ms), the duration of medium-duration fixations increases due to fatigue. The range of change in pupil diameter also increased during the task, since the expended forces increase [15]. The maximum speed of saccades and their duration decrease as the experiment progresses [15].

The work [16] examines changes in attention due to fatigue. The N-back test with distractors in the form of faces was used. The amount of time recorded off-screen became significantly higher at the end of the experiment. When changing the reward of participants for participating in the experiment, this effect became smaller, which indicates that an increase in the degree of fatigue is not always accompanied by a decrease in attention to the task and an increase in attention to distractors in the form of faces. The pupil diameter significantly decreased by the end of the test, and increased after a change in motivation.

In the work [17] on detecting fatigue by the characteristics of eye movements of soldiers in field conditions, the authors identify a number of parameters and their changes in connection with fatigue. The frequency and duration of blinks increase, and the interval between blinks decreases. However, the frequency of blinks at some point reaches a maximum value, and the fatigue value can continue to grow. The duration of blinks is a widely used parameter for fatigue detection.

In [18], a study of the behavior of excavator operators was conducted using an oculograph, a scene camera, and two eye-monitoring cameras. An excavator control simulator was used as a task. To achieve a state of fatigue, each participant performed the time on operating (TOO) task. The duration of the entire experiment was 100 minutes, including training, 5 TOO tests, and a break. The main part of the experiment was the execution of the excavator operator's daily tasks, the remaining part was taken up by the hazard detection task (HDT), which required participants to respond to a visual stimulus to identify dangerous behavior. This test consisted of detection the hazard level of a person's location using rear-view mirrors. The following parameters were selected to detect fatigue: blink frequency and duration, pupil size, and gaze direction. The analysis results showed an increase in blink frequency, a decrease in pupil diameter, and a decrease in the operator's attention.

Thus, according to the literature analysis, the most popular and reliable parameters of oculomotor events for detecting fatigue are saccadic indicators (peak and average speed, duration). Such characteristics as blink frequency and duration are also often used. A number of parameters are contradictory for detecting the state of fatigue and most likely, multidirectional changes in parameters depend on the context and state in which the operator is, for example, the nature of the work performed.

III. EYE MOVEMENT DATASET

When developing the session, two groups of tasks were used that differ in response style - passive and active. Assessing involvement, the degree of attention - reading a text, and requiring a coordinated motor response: go/no-go task, test "Landolt rings", "Tetris" game. As a task reproducing the natural and everyday activity of the operator, a task for reading a scientific text was used. The length of one experimental session is 60 minutes. Since the operator would have different levels of fatigue at the beginning and end of the recording session, the go/no-go task was conducted at the beginning and end of the experimental session.

The go/no-go task was recorded programmatically upon presentation of the target stimulus, a red circle, and the distractor, a green circle. The participant's task is to press a button when the target stimulus appears. The number of trials is 70. The following parameters are recorded: average reaction time, standard deviation, and number of errors. Reading a scientific text serves as a control and static load condition. Articles and books on the subject of interest to the participant were published in peer-reviewed journals and found through an indexed database. The participant reads the text from the monitor for 15 minutes. The "Landolt rings" test is a test used to measure visual acuity, consisting of symbols in the form of an incomplete ring [19]. The size of the table presented is 30x30, 5 minutes are allocated for passing the test. The following parameters are recorded: time spent, number of target symbols, number of detected symbols, number of missed symbols, and number of errors. These parameters allow calculating the coefficient of mental performance. The "Tetris" game acts as a control and dynamic loading condition. For 15 minutes, the participant plays the classic version of the "Tetris" game using the keyboard.

Thus, the experimental session, which consists of the following points:

- Completing the VAS-F questionnaire
- The go/no-go task (active task)
- Reading a scientific text (passive task)
- Test "Landolt rings" (active task)
- Test playing "Tetris" game (active task)
- The go/no-go task (active task)

During the execution of each task, eye movements are recorded. The recording was stopped after the task was completed. Fig. 1 shows the sequence of tasks in one session. The total duration of such recording is 1 hour.

During one day, the participant performs 3 recording sessions. Before each session, the VAS-F questionnaire is filled in. Participants were required to record a dataset consisting of 8 days, however, not all of them managed to do so. Each participant's set consists of recordings of at least one day. In the experiments on forming the dataset [20], 15 people took part, in total 192 hours of recording were obtained.

IV. ALGORITHM FOR DYNAMIC DETECTION OF PC OPERATOR FATIGUE

Fig. 2 shows the developed algorithm for fatigue detection using gaze coordinates and eye movement characteristics. Eye movement characteristics are calculated based on gaze coordinates and after correlations with test results, experts selected speed characteristics, the proportion of characteristics from the total number, saccade length characteristics, and characteristics of the curvature of the gaze movement trajectory.

To select the best classifier for each algorithm, it was necessary to evaluate the achieved accuracy. To improve the performance of the classifiers, normalization was applied to each characteristic. To do this, the mean value was subtracted from each characteristic and the result was divided by the standard deviation. To prepare for the cross-validation process, the gaze coordinates and selected characteristics are divided into five equal consecutive parts and five different sets of training and testing samples are collected.

Then the "selected characteristics" and "gaze coordinates" modules are transferred to the "learned model" module, which contains one classifier such as random forest, decision tree, and multilayer perceptron. And as a result of the work of one of the three algorithms, fatigue is detected.

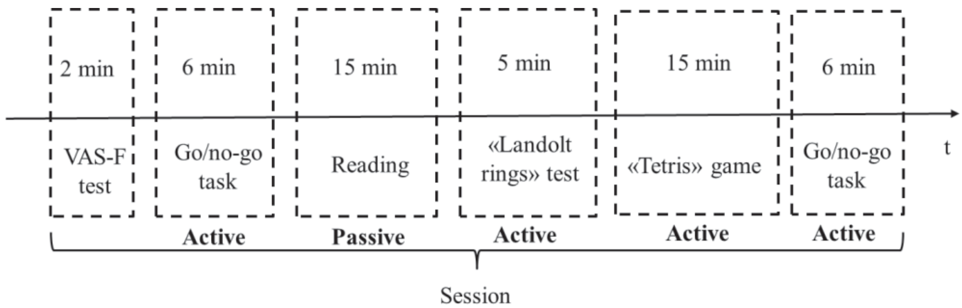

Fig. 1. Timeline of one recording

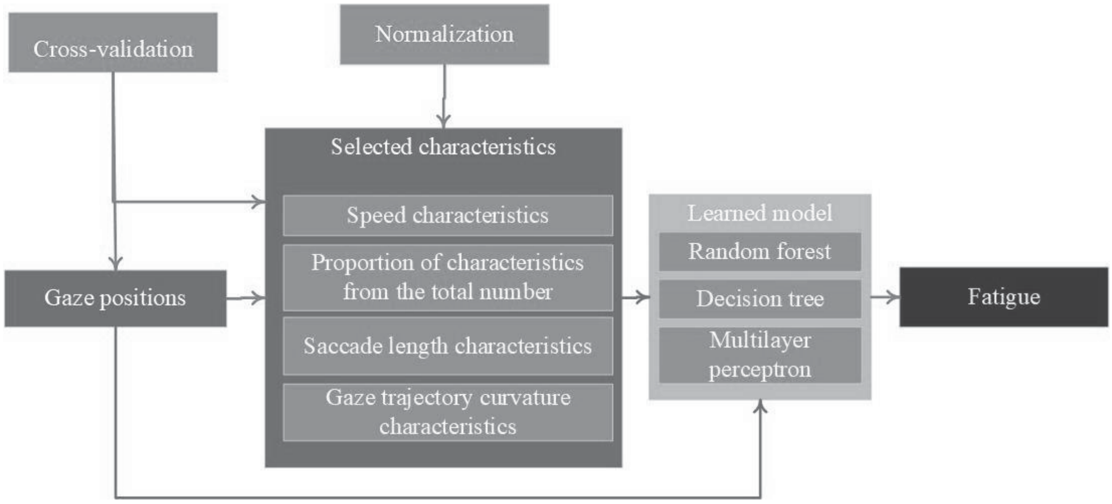

Fig. 2. Fatigue detection algorithm

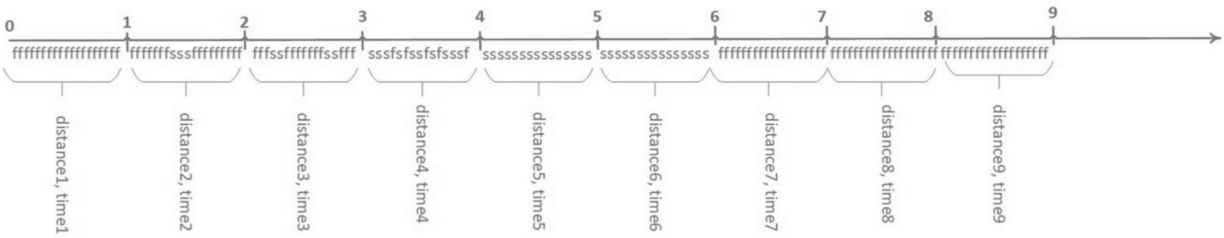

Fig. 3. Gaze speed in time intervals

Speed characteristics characterize how quickly the gaze moves. Proportional characteristics characterize the proportion of characteristics from the total number, for example, the percentage of fixations shorter than 150 ms from the total number of fixations. Saccade length characteristics characterize the average, minimum, maximum length of a saccade. Characteristics of the curvature of the gaze trajectory characterize the ratio of the path traveled by the gaze to the movement of the gaze.

Calculation of the minimum/maximum gaze speed in a second interval (min_speed/max_speed) is shown in Fig. 3. The path traveled by the gaze ($distance_1$) and the travel time ($time_1$) for the first time interval are calculated. Then $distance_1$ is divided by $time_1$ to obtain the speed for the first time interval ($speed_1$). The speed for the second time interval is calculated similarly, etc. The minimum/maximum gaze speeds in a time interval are calculated by enumerating all speeds. The average gaze speed in a time interval (average_speed) is calculated by dividing the path for all time intervals (all_distance) by the number of all time intervals (time_interval). Calculation of the average curvature of the gaze trajectory (average_curvature) is shown in Fig. 4. The gaze movement is the vector connecting the initial and final positions of the gaze, the path traveled is the length of the trajectory. The curvature is calculated for 4-second intervals. The path traveled by the gaze ($path_1$) is divided by the gaze movement ($movement_1$) during the first 4-second interval, and the first curvature value ($curvature_1$) is obtained. Then the second curvature value ($curvature_2$) is calculated for the second 4-second interval. The minimum (min_curvature) and maximum (max_curvature) curvature values are found by enumerating all curvature values. All curvature values for all 4-second intervals are summed up (all_curvature) and divided by their number (curvature_counter). This yields the average curvature value.

The entire dataset was labeled based on the results of the “Landolt rings” test [21]. One of the parameters of this test is “mental performance”. The values of this parameter within this dataset were in the range from -0.5 to 4. To train the neural networks, the numerical values of the target variable - mental performance - were transformed into categories. Thus, mental performance was classified as “low” or “high” based on the selected threshold of “1.5”. This threshold was chosen because this value allows all the data to be divided into equal proportions. If the subject had a mental performance value of 1.5 or higher, then his performance was considered “high”, otherwise - “low”.

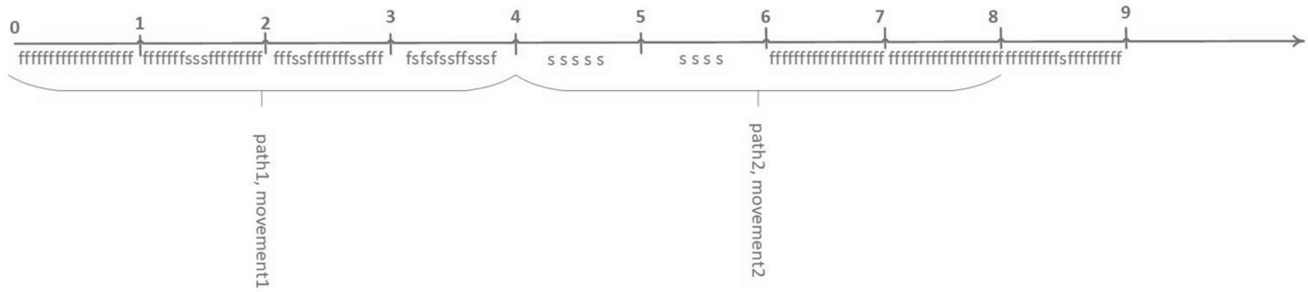

Fig. 4.Calculation of gaze trajectory curvature

V. RESULTS

The main indicator of the quality of the evaluation performed is the F-score, which is a set of accuracy and recall of the estimates issued by the classifier. Experiments were conducted using various sets and combinations of groups to study the effect of specific groups of characteristics on the classification efficiency. The goal was to determine whether using one group or a combination of several groups would give better results. Three classifiers and three sets of parameters were used for the task, namely: group 1, group 2, group 3, presented in Table I. Seven characteristics were calculated from the eye movement data in x and y coordinates, namely:

- average value;
- standard deviation;
- minimum value;
- maximum value;
- 25th percentile;
- 50th percentile;
- 75th percentile.

These calculated characteristics will be referred to as group 1. The next step of data analysis involved selecting a suitable subset of eye characteristics from the 51 available characteristics present in the dataset for each recording. To identify relevant characteristics, a Wilcoxon test was used, considering those characteristics that had a p-value less than or equal to 0.05 when compared with the mental performance value. The selected characteristics were combined into group 2, are as follows:

- average gaze speed inside fixation area, °/sec;
- minimum gaze speed inside fixation area, °/sec;
- fixations number with duration between 150 ms and 900 ms;
- proportion of time spent in fixations between 150 ms and 900 ms, %;
- average curvature of gaze trajectory;
- minimum curvature of gaze trajectory;
- maximum curvature of gaze trajectory;
- minimum gaze speed in second interval, °/sec;
- minimum saccade length, °;
- maximum saccade length, °;
- maximum saccade speed, °/sec;
- fixation number less than 180 ms per minute;
- fixation number more than 150 ms per minute;
- fixation number more than 900 ms per minute;
- false fixation number per minute;
- average acceleration in second interval, °/sec²;
- fixation number less than 150 ms per minute;
- average saccade speed, °/sec;
- proportion of fixations with duration more than 180 ms, %;

TABLE I. RESULTS OF EXPERIMENTS

Characteristics	Algorithm	F-score	Accuracy
Group 1	Random forest	0.84	0.80
Group 2	Random forest	0.84	0.79
Group 3	Random forest	0.84	0.80
All groups	Random forest	0.84	0.79
Group 1 + Group 3	**Random forest**	**0.85**	**0.80**
Group 1	Decision tree	0.77	0.73
Group 2	Decision tree	0.78	0.73
Group 3	Decision tree	0.76	0.72
All groups	Decision tree	0.76	0.74
Group 1 + Group 3	Decision tree	0.77	0.73
Group 1	Multilayer perceptron	0.83	0.78
Group 2	Multilayer perceptron	0.83	0.79
Group 3	Multilayer perceptron	0.83	0.78
All groups	Multilayer perceptron	0.83	0.78
Group 1 + Group 3	Multilayer perceptron	0.83	0.77

- proportion of fixations with duration less than 180 ms, %;
- proportion of fixations with duration more than 180 ms, %;
- proportion of fixations with duration less than 180 ms, %;
- average saccade duration, sec;
- average saccade length, °;
- proportion of fixations with duration between 150 ms and 900 ms, %.

The following eye movement characteristics were selected by experts based on the analysis and discussion of the experimental results and were included in group 3:

- average curvature of gaze trajectory;
- minimum curvature of gaze trajectory;
- minimum saccade length, °;
- proportion of time spent in fixations less than 150 ms, %;
- proportion of fixations with duration less than 150 ms, %;
- average gaze speed inside fixation area, °/sec;
- maximum gaze speed inside fixation area, °/sec.

VI. CONCLUSION

Thus, in order to evaluate the performance of the proposed classification models, three different classifiers with different parameters were investigated. In addition, principal component analysis (PCA) was applied to improve the performance. In numerous experiments, each characteristics group was systematically studied separately and in combination with other groups to identify the most effective combination. Also, several test set strategies were used to comprehensively evaluate the models. First, a test set was randomly selected to evaluate the performance of different models and characteristics. Then, a balanced test set was created based on the actions performed during the sessions. The results of these experiments showed that using the characteristics of Group 1 and Group 3 in the random forest based classifier gave the most promising results. This approach achieved the highest F-score and the best average accuracy, indicating the overall robustness of the model.

For the future work we will increase the number of experiment participants to increase the F-score and accuracy of classification models and improve fatigue detection algorithm. The limitations of this algorithm is using for professions in that the worker sits at his workplace and his gaze is directed at the monitor.

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