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Identification Approach for Biometric Systems Using The ABM Procedure with The Low Frequency Eye Tracker

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Abstract — *Biometric Systems Now a Days are playing a vital role* in the whole word. Biometric Identification is being carried out in all the industrics, Institutions and in all the concerns wherr we are in need of the security and heavy monitoring. There are various traints considered for identifying and Authenticating the individual persons, they may include the behaviourial and also the physiological traits. Eye tracking is the process of measuring either the point of gaze (where one is looking) or the motion of an eye relative to the head. An eye tracker is a device for measuring eye positions and eye movement. Eye trackers are used in research on the visual system. This paper focuses on the identification with low frequency Eye Tracker. he most widely used current designs are video-based eye trackers. A camera focuses on one or both eyes and records their movement as the viewer looks at some kind of stimulus. Most modern eye-trackers use the center of the pupil and infrared / near-infrared non-collimated light to create corneal reflections (CR). The vector between the pupil center and the corneal reflections can be used to compute the point of regard on surface or the gaze direction. A simple calibration procedure of the individual is usually needed before using the eye tracker. This paper presents a review of the related works in the field as well as a general classification of different identification types. We stated a formal description of a saccade and an analyzed fragment of the gaze trajectory containing a saccade, which is based on the finite differences method, and revealed features of the eye movements that can be used for the identification purpose. Two classifiers are proposed and compared based on the experimental results obtained for them and we examined whether the delivery of an attentional bias modification (ABM) procedure in the presleep period could produce transient benefits for sleep-disturbed individuals by reducing presleep cognitive arousal and improving ease of sleep onset. These results suggest that delivery of ABM can attenuate cognitive arousal and sleep onset latency and highlights the possibility that targeted delivery of ABM could deliver real-world benefits for sleep-disturbed individuals.

***Index Terms*— ABM, authentication, biometrics (access control), identification of persons.**

I. INTRODUCTION

Fig. 1. Eye as a dynamic system.

Identification are assessed by analyzing his gaze trajectory registered by the eye tracker.

One of the most perspective fields of the eye movement studies is the dynamic biometric identification, e.g. [18]– [22]. Nowadays, with fast development of information technology, we cannot imagine our lives without different information systems facilitating access to various information resources. Access to a large amount of such systems must be protected and opened only to the registered and confirmed users. Thus, high accurate identification modules should be embedded in these information systems. Identification methods can be classified into three categories [23] based on the used factors:

- User's knowledge
- User's ownership
- User's biometric characteristics
  - Physiological characteristics
  - Behavioral characteristics

Many types of biometric identifiers are available now and used in different systems, e.g. fingerprint [24] or palm pattern analysis [25], ear [26] or iris [27] recognition, electrocardio-gram (ECG) analysis [28], keystroke dynamics [29], face [30], gait [31] and body parts [32] recognition, etc. Human eyes constitute a rich source of information to identify a person. An eye movement is a non-visible, complex and unique feature that provides unrepeatable biometric data including specific behavioral characteristics. Therefore, this feature may become one of the most secure types of biometric identification. Moreover, eye tracking data can be used in order to determine the level of person's skills in a particular field.

Human eye can be viewed as a dynamic system (Fig. 1), which is influenced by some stimuli as an input and produces gaze trajectory, which can be detected by the eye tracker, as an output. The eye possesses different characteristics, e.g. velocity, acceleration, etc. Different studies had been con-ducted, performing analysis of such characteristics [19], [22]. Authors combine them with some other features provided by the gaze trajectory and investigate their influence on the performance of person identification methods based on eye tracking techniques. However, currently such identification methods do not provide good accuracy for revealing person's identity and various studies are conducted in order to constitute the best method including examination of the gaze trajectory through using different stimuli [19] or carrying out compe-titions [33], [34]. Thus, person identification based on eye tracking techniques attracts interest of many researchers from all over the world.

Eye trackers are technical devices that consist of two parts: software and hardware. In the most studies high-frequency eye trackers are used, providing frequency of 120 Hz and higher. Higher sampling rate produces the eye trackers that have more complicated hardware. Some authors describe application of the handmade eye trackers based on a camera, though its frame rate is also very high (e.g. in [18] 500fps camera had been used). A valid application of low-frequency eye trackers is of great interest and in our current study, as well as in previous one [35], we used 30Hz eye tracker, which sampling rate is almost the same as normal camera's frame rate (25 fps).

In this work, we propose a new identification approach based on eye tracking techniques and present the results of its performance, obtained after conducting experimental study in ITMO University. The second section describes works of other authors in the field of revealing person's identity using eye tracking data, the third section describes our identification approach, section IV provides information about participants and the study design, and section V presents the results.

II. RELATED WORK

Various methods of person identification based on eye tracking techniques have been introduced during the last few years. An accuracy of the applying methods is evaluated by calculating different types of errors, e.g. false acceptance rate (FAR), false rejection rate (FRR) or half total error rate (HTER) based on the combination of the two errors mentioned above [36], [37]. FAR is defined as a number of false acceptances for the classification result to the amount of impostors, while FRR is defined as a number of false rejections to the amount of client accesses. HTER combines these two error types and is defined as a half-sum of FAR and FRR. Many authors also consider equal error rate (EER) that is calculated at the point, where FAR is equal to FRR. Another accuracy evaluating method is constructing Receiver Operating Characteristics (ROC) curves [37], [38] – the curves based on FAR and FRR measures for observing values.

Different equipment is used for collecting eye tracking data in the studies of biometric identification based on the eye movement analysis. However, almost all of such equipment has complex hardware due to the provided high sampling rate, e.g. a 120Hz eye tracker used in [19] and [22] or 500 fps camera in [18]. Eye tracking data is collected using different stimuli showed to participants during the experimental studies. Four stimuli had been used in [19], i.e. two of them contained a dot panel and participants were asked to reproduce a specific dot path only by looking at particular dots, the third stimulus consisted of three linear graphs asking participants to follow each of them, and the fourth stimulus was a picture. One of the most frequently used stimulus in eye tracking studies is a jumping dot [18], [20].

In some studies, [19], [21] the dynamic features of the eyes, e.g. eyes velocities and accelerations are considered. Some methods refer to the parameters of only one of the available gaze types, e.g. saccades' amplitude, velocity, acceleration [18], [20], [22].

After computation of necessary parameters has been finished, a particular classifier is applied to perform datasets classification. Different classifiers are used in the experimental studies and then accuracy for their performance is calculated and analyzed. A majority of the authors considers HTER values in order to calculate error rate of their identification method and some authors [21] observe ROC curves based on the calculated FAR and FRR values. Naïve Bayes (NB) [39] and k-Nearest Neighbor (kNN) [40] classifiers are the ones of the most frequently applied. In [20] both Naïve Bayes and kNN classifiers had been observed and then the calculated errors had been compared. Application of the Naïve Bayes classifier achieved 13% and 3% HTER for different conditions, when accuracy for the kNN classifier was a little lower with minimum HTER of 10%, eye movements data for this study had been registered with the Electro-Oculographic (EOG) signal. In [21] kNN classifier had been applied, as well as Support Vector (SV) and Fisher classifiers, and achieved 3% HTER for 80% of the training data, while SV and Fisher classifiers performed better and achieved 1% and 0% error rate.

As described above, it can be noticed that experimental studies are mostly conducted using high-frequency eye track-ers with sampling rate of 120 Hz or higher, i.e. 500 fps camera in [18], 120Hz eye etracker in [19] and [22], 400Hz EOG system in [20], and 50Hz device in [21]. However, this leads to the more complicated device's hardware base. Thus, one of the most important aims of our study is to reveal whether it is possible to provide accurate person identification results by processing data obtained from a low-frequency eye tracker.

III. BIOMETRIC IDENTIFICATION APPROACH

A. Formal Saccades Description

Saccades are fast movements of the eyes, with a typical duration of 30-100 ms and a latency of 100-300 ms [2]. Most of the modern eye trackers use adaptable velocity threshold filters in order to distinguish saccades and fixations.

Our approach, which is represented in this paper, is based on the analysis of fragments containing a saccade. At first a saccade should be recognized and extracted from the raw signal. The velocity thresholds, described above, are used for this purpose. The applied threshold in our experimental study equaled 30° /s. A continuous time representation of a considered fragment with a saccade with an amplitude of

9 degrees is depicted in Fig. 2: it shows changes in the coordinates of the gaze position during a time – $x^j(t)$ – in $A^j x^j y^j$ coordinate system, which is based on the gaze trajectory of the j^{th} saccade. Gaze trajectory starts at the point A^j – the first point of the considered fragment of the gaze trajectory, and ends at the last trajectory point B^j as presented in Fig. 3. $A^j x^j y^j$ coordinate system is rotated along the fragment's gaze path at α^j angle against the main $A^0 x^0 y^0$ coordinate system of the screen.

While a person is viewing the stimulus, e.g. a text, an image, a movie, etc., his gaze trajectory consists of many fixations and saccades. As we consider fragments containing saccades in specified coordinate systems, they can be viewed as presented in Fig.4. In this graph, A^j and B^j are the first and last points of the j^{th} fragment, $j = 1,2,\ldots,n$, $A^j x^j y^j$ is a corresponding coordinate system for each fragment and α^j is an angular orientation of the j^{th} frame.

Mainly eye tracker determines a saccade as a regarded type of the eye movement after applying velocity thresholds computed in degrees per seconds based on the coordinates

TABLE I

LENGTH OF FRAGMENTS COLLECTED WITH LOW-FREQUENCY EYE TRACKER

Number of points in fragments	Percent of fragments
5 points	72.26 %
6 points	22.79 %
7 points	3.65 %
8 points and more	1.30 %

the eye position in space and gaze coordinates on the screen. When we consider a fragment depicted in Fig. 2, it will be determined as a saccade only in the middle area of the fastest gaze movement's speed transition. For example, sampling of the fragment shown in Fig. 2 is presented in Fig. 5. In that case, from the five points

$$x_1^j = x^j(t_1),$$
$$x_2^j = x^j(t_2),$$
$$x_3^j = x^j(t_3),$$
$$x_4^j = x^j(t_4),$$
$$x_5^j = x^j(t_5)$$

of the gaze trajectory, four points x_1^j, x_2^j, x_4^j, x_5^j will be determined as fixations by the eye tracker and point x_3^j will be stated as a saccade. Moreover, most of the fragments collected with the low-frequency eye tracker will last for approximately 130 ms or 5 points. The distribution of fragments' lengths for datasets collected with 30 Hz eye tracker is presented in Table I. Hence, we have only five points for the analysis. As we consider such a low number of points, it should be men-tioned, that the first point x_1^j in the applied $A^j x^j y^j$ coordinate system is always used as a reference point and equals to zero, as shown in Fig. 5. Hence, each j^{th} fragment is described by four points: x_2^j, x_3^j, x_4^j, x_5^j. To restore the considered fragment in continuous time, it should be approximated by applying the finite difference method based on a Taylor series:

$$x^j(t_i+\tau) = x^j(t_i) + \frac{(x^j(t_i))'}{1!}\tau + \frac{(x^j(t_i))''}{2!}\tau^2 + \ldots + \frac{(x^j(t_i))^{(m)}}{m!}\tau^m + \ldots \quad (1)$$

where $i = 2,3,4,5$, $\tau = t - t_i$,

$$(x^j(t_i))^{(m)} = \frac{\nabla^m x_i^j}{h^m} + O(h), \quad (2)$$

$\nabla^m x_i^j$ is a finite backward difference of the m^{th} order, $h > 0$ is a sampling interval.

Accuracy of the described fragment approximation depends on the number of terms used in Taylor series as well as on the derivative calculation way. If the way of computing derivatives is based on the finite differences, an error will have a linear dependence on the sampling interval h. In case of applying 30Hz eye tracker, only the presented in Fig. 6 finite backward differences that can be determined on basis of points x_2^j, x_3^j, x_4^j, x_5^j, together with these points, might be considered as fragment's characteristics. Moreover, it should be men-tioned, that these measurements are obtained with stochastic effects, e.g. cause of a sampling rate deviation, finite accuracy of determining gaze position, etc. Such a problem also exists in motion control [42].

Thus, biometric identification using low-frequency device states the nondeterministic problem of the identification under conditions of insufficient measure-ments that requires formation of the nontrivial approaches and algorithms.

Researchers have used a wide range of methods borrowed from cognitive psychology to examine attention bias to threat in individuals with Generalized Anxiety Disorder (GAD;Mathews & MacLeod, 1985, 1986; MacLeod, Mathews, & Tata, 1986; Mogg, Millar, & Bradley, 2000). Research using these methods has consistently produced evidence that patients with GAD preferentially attend to threat relevant stimuli over neutral stimuli when the two compete for processing priority.

Participants were randomly assigned to one of two conditions: Attention Modification Program (AMP; n = 14) or Attention Control Condition (ACC; n = 15). The participants, independent assessors, and research assistants working with the participants were blind to participant condition. To maintain the blind, each participant received an envelope that contained a condition number that they entered into the computer to start the assigned computer program. Groups did not differ significantly on any clinician-administered or self-report measure at pre-training (ps > .2).

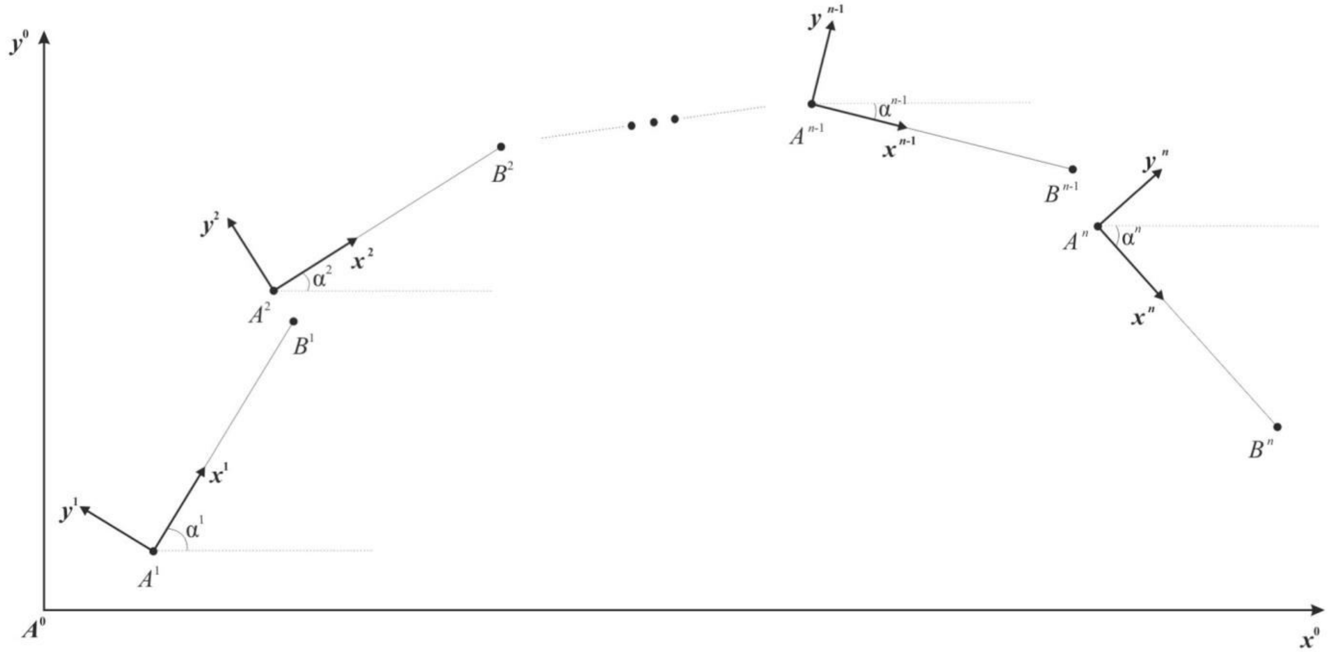


Fig. 4. Coordinate systems for different fragments.

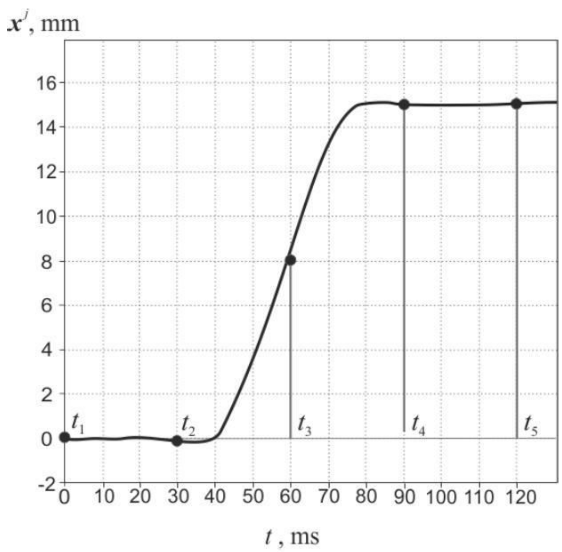


Fig. 5. Sampling of the considered fragment.

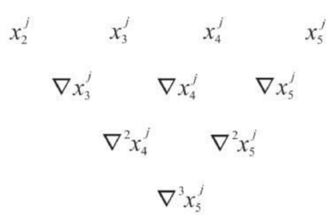


Fig. 6. Differences between fragment's points.

B. Features of the Eye Movements

In our study, eye movements' data is captured by the eye tracker with 30 Hz frequency and includes the following parameters: time (in ms), gaze type (fixation or saccade), gaze point coordinates (in mm) in $A^0x^0y^0$ coordinate system, eye position (in mm) in $A^0x^0y^0z^0$ coordinate system of the monitor, eye pupil diameter (in mm), etc. The presented approach is based on the analysis of characteristics of the eye movements collected for each person as datasets during the r th session. These characteristics might be determined based on the list of the following variables for each j th fragment:

1) Coordinates x_{2r}^j, x_{3r}^j, x_{4r}^j, x_{5r}^j
2) The first order differences

$$(x_{3r}^j) = \frac{\nabla x_{3r}^j}{h},\ (x_{4r}^j) = \frac{\nabla x_{4r}^j}{h},\ (x_{5r}^j) = \frac{\nabla x_{5r}^j}{h}$$

3) The second order differences

$$(x_{4r}^j) = \frac{\nabla^2 x_{4r}^j}{h^2},\ (x_{5r}^j) = \frac{\nabla^2 x_{5r}^j}{h^2}$$

4) The third order difference

$$(x_{5r}^j) = \frac{\nabla^3 x_{5r}^j}{h^3}$$

5) Pupil diameter ρ.

All the mentioned variables are dynamic quantities as they describe different aspects of the eye movements. Pupil diameter is also often observed by many authors in medical and psychology field as one of the most accurate measures of

TABLE II

EVALUATING STATIONARITY FOR VARIABLES: P-VALUES FOR TESTS

Variable	Chi-square	Paired t-test	Kolmogorov-Smirnov test
ρ	**0.000072**	**0.0201**	**0.0491**
$x^j_{2_r}$	0.586305	0.4855	0.4921
$x^j_{3_r}$	0.294832	0.3321	0.4935
$x^j_{4_r}$	0.108162	0.0794	0.3781
$x^j_{5_r}$	0.052011	0.0790	0.3570
$(x^j_{3_r})'$	0.505074	0.4155	0.4618
$(x^j_{4_r})'$	0.280757	0.3320	0.5392
$(x^j_{5_r})'$	0.140377	0.3297	0.4458
$(x^j_{4_r})''$	0.064949	0.0592	0.4903
$(x^j_{5_r})''$	0.256798	0.5494	0.5272
$(x^j_{5_r})'''$	0.339146	0.5225	0.5067

person's functional state or reaction to some stimuli, which can be used for affective computing [43], [44]. Analysis of which of the stated variables can be applied for the identification purpose is given further.

We have tested all the described above variables for their stationarity, as this characteristic is obligatory, if they are used for the identification purpose. The test set included 325 datasets collected during the experimental study with about 40000 fragments extracted. Three methods had been applied to evaluate the hypothesis of stationarity, i.e. methods based on chi-square and Student's statistics and Kolmogorov-Smirnov test. P-values for tests are presented in Table II. All the hypotheses had been evaluated at 5% significance level.

All the presented methods were tested on datasets collected with 30 Hz eye tracker. These datasets had been divided into two equal parts. Firstly, we applied a chi-square test, which is based on the expected and observed values. We considered a number of points greater or less than mean of each dataset's part as the observed values. The expected values were presented as the number of points greater or less than a mean for a whole dataset in relation to the currently observed one. After values for all datasets had been calculated, a chi-square statistic was computed and compared to the basic chi-square value at 5% significance level. The second method – paired t-test – was applied for the differences between a number of points greater than mean of each part of a particular dataset. After that, Student's statistic was calculated based on the mean and standard deviation of previously computed set of differences, which then was compared to the basic Student's t-statistic value. Kolmogorov-Smirnov test was applied for two parts of each dataset separately. The resulting p-value was calculated as mean of the probabilities of each variable for all datasets.

As shown in Table II the only variable that rejects the stationarity hypothesis at 5% significance level is pupil diameter. shown in Fig. 7. These graphs represent changes in the mean values of pupil diameter using moving average method with window equaled 30ms, and confidence intervals as vertical lines. Such differences depend on the physiological parameters of the pupil during its adaptation to the environment and can be caused by changes in person's functional state, i.e. by cause of fatiguability, cognitive overload, decrease of working capacity, etc., and, therefore, the obtained results for this feature are as expected. Hence, in our approach we assume the following 10 features calculated for each fragment:

- $x2^j_r$, $x3^j_r$, $x4^j_r$, $x5^j_r$
- $(x3^j_r)$, $(x4^j_r)$, $(x5^j_r)$
- $(x4^j_r)$, $(x5^j_r)$
- $(x5^j_r)$

Its values are marked in the table in bold. The variability of pupil diameter values for different datasets is also

C. Identification Algorithms

The proposed algorithms are based on k-Nearest Neighbors and Naïve Bayes classifiers. These algorithms are described in details in the next subsections. General schema of the identification algorithm is presented in Fig. 8. The main hypothesis of our algorithm is that the determined in previous subsection unique features can identify a person, and the distribution for a specific feature for all fragments of each dataset is not changing throughout a time. Hence, person's identity can be authenticated, whenever he tries to enter the system.

In the algorithm we assume that there is a data storage, where datasets are kept with a relation to each person they were collected for. Let I be a set of datasets' indexes. Then $C_s \subset I$ is a subset of datasets' indexes for particular person, called s^{th} class. Each r^{th} dataset is described by a set of 10 features $\xi_r = \{\xi_{r,1}, \xi_{r,2}, \dots, \xi_{r,10}\}$, where:

$\xi_{r,1} = \{x2^j_r\}$, $j = 1, 2, \dots, n_r$,

$\xi_{r,3} = \{x3^j_r\}$, $j = 1, 2, \dots, n_r$,

$\xi_{r,4} = \{x4^j_r\}$, $j = 1, 2, \dots, n_r$,

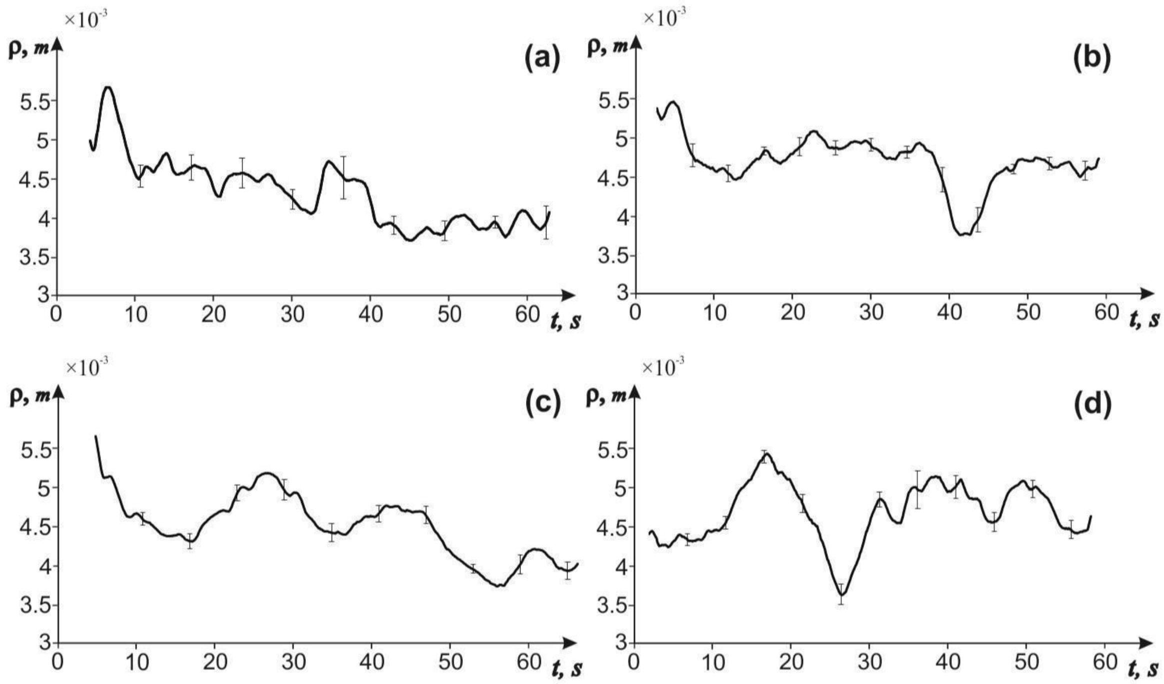
$\xi_{r,5} = \{x5^j_r\}$, $j = 1, 2, \dots, n_r$,

$\xi_{r,10} = \{(x3^j_r)\}$, $j = 1, 2, \dots, n_r$,

and n_r is a number of fragments in r^{th} dataset.

Both of the proposed algorithms consider the same idea of calculating a distance between a dataset and s^{th} class in order to determine the class, a dataset is related to. However, the computation formulas for the distance and final decision rules differ.

1) Paired Comparison Algorithm: The algorithm based on k-Nearest Neighbors classifier involves the use of the following formula for calculating distance between r^{th} and q^{th}



datasets in the i^{th} feature:

$$d(\xi_{r,i}, \xi_{q,i}) = -\ln p\left(K \ge \sqrt{\frac{n_r n_q}{n_r + n_q}}\, D^i_{r,q}\right) \quad (3)$$

where K is a random variable of Kolmogorov distribution,

$$D^i_{r,q} = \sup_{\xi} \left| F^i_{r,n_r}(\xi) - F^i_{q,n_q}(\xi) \right|$$

is a Kolmogorov-Smirnov test statistic for i^{th} feature of the r^{th} and q^{th} datasets, $F^i_{r,n_r}(\xi)$ and $F^i_{q,n_q}(\xi)$ are empirical distribution functions for the r^{th} and q^{th} datasets. Hence, a distance between two datasets considering all necessary features can be expressed as:

$$d(\xi_r, \xi_q) = \sum_{i=1}^{10} d(\xi_{r,i}, \xi_{q,i}). \quad (4)$$

The distance between the C_s class and r^{th} dataset is calculated by:

$$d(\xi_r, C_s) = \min_{q \in C_s} [d(\xi_r, \xi_q)]. \quad (5)$$

The whole list of actions performed during application of the algorithm is described further.

The first step is collecting eye-tracking data for a person. Particular stimulus is shown on the screen, and the task, which corresponds with the stimulus, is given to a person. While he is dealing with the task, necessary eye tracking data is collected.

As our approach is based on the saccades' analysis, the next step is to extract necessary fragments from the collected

The most important step before classification is performed, is the computation of eye movements' features. As described above, we have determined 10 features, namely: coordinates for four points, the first order difference for three coordinate points, the second order difference for two points and one third order difference.

The next step is performing classification itself. Before the comparing collected dataset with datasets stored in database. Kolmogorov-Smirnov test is applied for each feature separately for the pairs of datasets, which consist of the collected dataset and one dataset from database. After the step had been finished, we obtain arrays of probability values for all performed comparisons.

The decision rule for this algorithm is based on the distance value computed by (4) for pairs of datasets based on the calculated Kolmogorov-Smirnov test probabilities. All distances are stored in array. Hence, after this step we have a map of distances from the collected dataset to all datasets stored in a database and indexes of the corresponding classes, containing these datasets. This map is then sorted based on the distances' values in an ascending way.

As we consider the presented algorithms to be possibly applied in real systems we should take into account that system may be attacked by impostors. Hence, in order to prevent a security violation, thresholds could be computed for all classes in order to remove datasets with high distance values from current observation. Thresholds are computed by the following formula:

$$d^* = \max d(\xi_r, C_s\ r), \quad (6)$$

dataset. As mentioned earlier, we consider five points for each fragment. Hence, after this step had been finished, we obtain a data structure with all the extracted fragments.

where d^*_s is a threshold for the s^{th} class (C_s), $d(\xi_r, C_s \setminus \{r\})$ is a distance from r^{th} dataset to the s^{th} class.

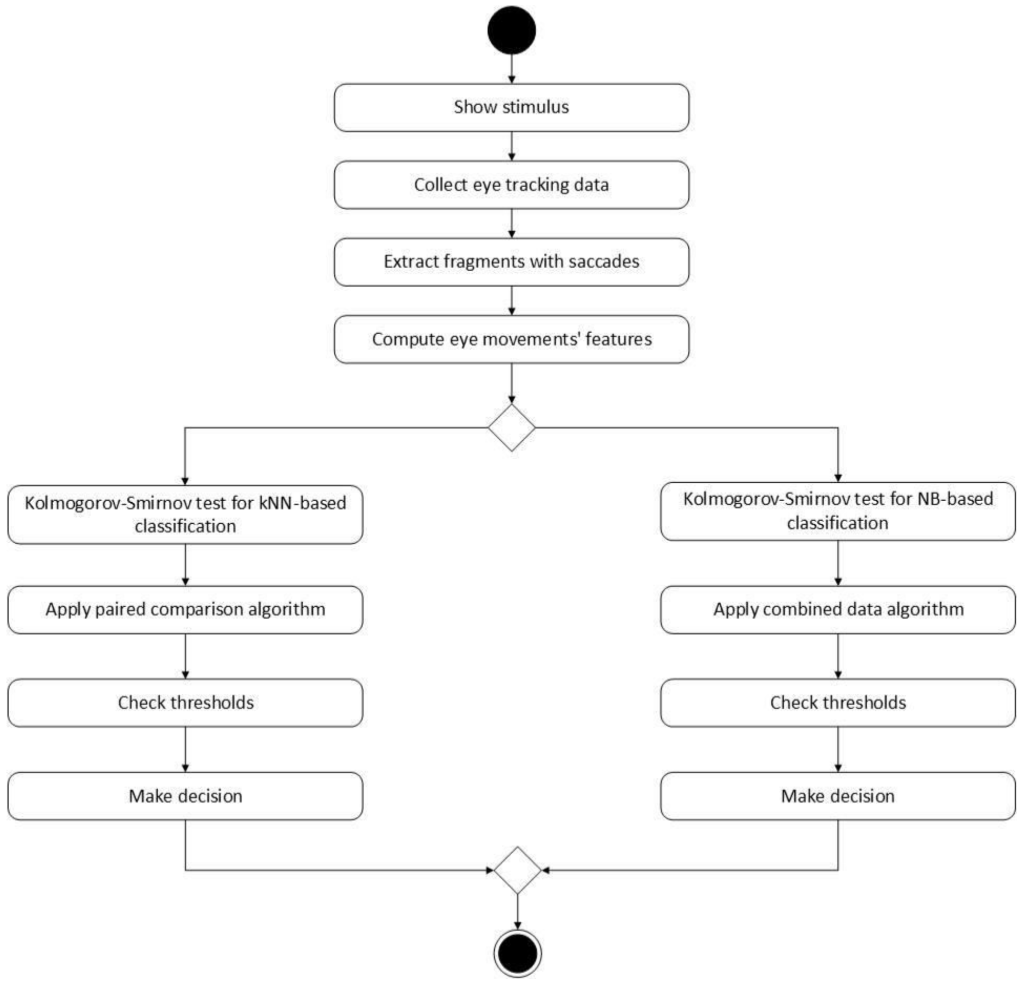


Fig. 8. Scheme of the identification algorithm.

The indexes of classes are kept in the aforementioned map for checking thresholds. If the first distance value from a dataset to the class is higher than the threshold for this class computed by formula (6), then this class is not considered and all distances for its datasets are removed from the map.

The final decision is made based on the resulting distances map and a particular k – number of datasets to count for C class before a dataset is considered being related to this class. Hence, the result of identification is a class with k-nearest datasets to the currently observed one. Number of operations to be performed by kNN-based algorithm can be compared to the number of datasets in a database.

2) Combined Data Algorithm: The second proposed computed:

features ξ_r being related to the class C_s, $p(C_s)$ is a probability of a dataset being related to the class C_s, $p(\xi_r)$ is a probability of a dataset having a set of features ξ_r. $p(C_s)$ and $p(\xi_r)$ are computed by the following formulas:

$$p(C_s) = \frac{|C_s|}{\sum_s |C_s|}. \tag{8}$$

$$p(\xi_r) = \sum_s p(C_s) \prod_{j=1}^{10} p(\xi_{r,j}|C_s). \tag{9}$$

Based on the presented formulas, a distance $d(\xi_r, C_s)$ from the r^{th} dataset with a set of features ξ_r to the s^{th} class can be

TABLE III
EYE TRACKING SPECIFICATIONS

Eye tracking specifications	
Sampling rate	[28, 32] Hz
Sampling interval	[31, 36] ms
Freedom of head movement	50 × 36 cm
Operating distance	[40, 90] cm
Recommended screen size	25″ (16:9)
Gaze angle	36°
Measurement accuracy	0.4° – 1.0°

1, 2, ..., 10. Therefore, Kolmogorov-Smirnov test is launched with sets of values for each feature for currently observed dataset and combined sets computed by the aforementioned combination formula for classes.

First steps of combined data algorithm are the same as in previously described paired comparison algorithm, i.e. showing stimulus for a person in order to collect eye tracking data, extracting fragments with saccades and computing necessary eye movements' features.

After all these steps had been finished, Kolmogorov-Smirnov test is applied for a dataset and classes from database. Probability values of Kolmogorov-Smirnov test are used in order to compute a distance from a dataset to each class C_S . The next step is to calculate thresholds for all classes stored in a database the same way as in kNN-based algorithm by formula (6), though considering distance defined as described above. Thresholds are checked for all values and classes, and distances higher than the corresponding thresholds are removed from the map. Final decision is made on the basis of the resulting distances map. Dataset is related to the nearest class. Upper bound of the number of operations to be performed by NB-based algorithm corresponds with the number of observed classes.

Attention Modification Program (AMP)

During each session, participants saw 240 trials that consisted of the various combinations of probe type (E or F), probe position (top orbottom), and word type (Neutral or Threat). Of the 240 trials, 80 included only neutral words: 2 (probe type) × 2 (probe position) × 20 (word pairs). The remaining 160 trials included one neutral word and one threat word: 2 (probe type) × 2 (probe position) × 2 (threat word position) × 20 (word pairs). On trials where participants saw one neutral word and one threat word (i.e., 66% of the trials), the probe always followed the neutral word. Thus, although there was no specific instruction to direct attention away from threat word, on 66% of the trials the position of the neutral word indicated the position of the probe.

Attention Control Condition (ACC)

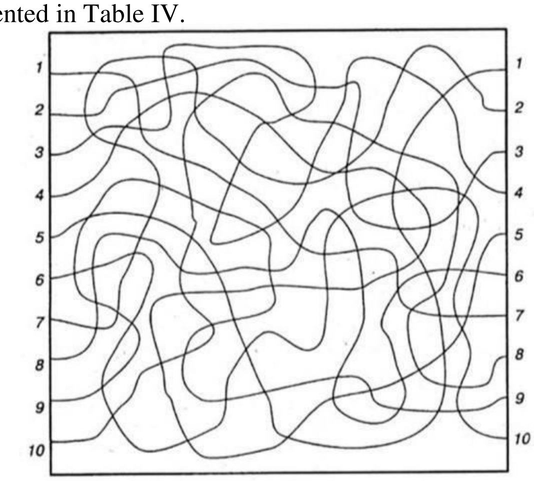
The ACC condition was identical to the AMP procedure except that during the presentation of the trials where a threat word was present, the probe appeared with equal frequency in the position of the threat and neutral word. Thus, neither threat nor neutral words provided information regarding the position of the probe, and there was no contingency between the position of either threat or neutral words, and the position of the probes.

IV. EXPERIMENT DESCRIPTION

Identification algorithms had been evaluated on the data collected during the experimental study, which had been conducted in ITMO University. The next subsections describe the equipment used in the experiments, participants involved and the procedures of the study.

A. Equipment

Experimental study had been conducted using low-frequency eye tracker Tobii X2-30, which provides sampling rate of 30 Hz. This eye tracker is a portable optical device, which was mounted on a monitor used for displaying experimental stimulus for participants during the test, when eye tracking data was collected. The calibration was done for each participant using a jumping dot stimulus before a test session. Specifications of the applied device are presented in Table III, which also shows a few types of device errors that can occur, e.g. a deviation of the sampling rate and sampling interval, non-observance of the distance limits by person, etc. Fragment of the raw data collected for a particular person is presented in Table IV.



B. Participants and Procedures

Experimental study had been conducted throughout a month. During this time, participants should have dealt with provided experiments, and eye tracking data had been collected for them and saved in a data storage as datasets with a relation to a person, who had currently passed an experiment. It was assumed that each participant could pass for about ten tests during the study. However, the stated number was not strictly required and the decision on how many experiments to take was up to a person.

An experiment for the study included a particular stimulus presented in Fig. 9. As our approach is based on the eye movements' features computed for the fragments with saccades, in order to get clear saccade data an implementation of A. Rey interwoven lines test had been used as stimulus. During the experiment each of the participants should have followed ten lines presented on the screen in turn. After a person had completed a test, the collected eye tracking data was saved.

As the experimental study was held in ITMO University, all the participants were first-year engineering students. In total, 45 participants were engaged in the study. Total percent of the experiments taken by students is presented in Table V. Datasets collected for each person were considered as classes. During the study, 45 classes with total amount of datasets equaled 325 with about 40000 fragments with saccades were obtained and considered further in the main data analysis. The test took for about 1-1.5 minutes for a participant, when about 120 fragments were collected for each session. An example of a part of the collected raw signal is presented in Fig. 10.

Procedure

Participants were randomly assigned to one of two conditions: Attention Modification Program (AMP; n = 14) or Attention Control Condition (ACC; n = 15). The participants, independent assessors, and research assistants working with the participants were blind to participant condition. To maintain the blind, each participant received an envelope that contained a condition number that they entered into the computer to start the assigned computer program. Groups did not differ significantly on any clinician-administered or self-report measure at pre-training (*ps* > .2).

The stimuli used in the attention training were derived from words used by McLeod et al. (2002). These authors created two sets of 48 words that were relevant to fears of individuals with general anxiety (sets A and B) and two sets of 48 matched neutral words. In the current study, half of the participants in each group saw a particular word set during training (set A) and were then tested pre-training and post-training using the other word set (set B). Thus, the tests of attention were conducted on a different set of words than the one used during training. To ensure the relevance of the particular words used during training for each participant, we used an idiographic material selection procedure. Prior to training, we asked each participant to rate the emotionality (−3 to +3) of each of the words from the two sets. Twenty words that were rated as most emotionally negative by that participant from the training set were then used as the threat words in the training task. During testing, all words from the alternate set were used.

Participants were seated approximately 30 cm from the computer screen. Words were presented in the center of the screen, approximately 1.5 cm from one another in size 12 Arial font, for 500ms. Word pairs for each participant were presented in a different random order. The computer program was written in Delphi (Borland, Inc.) for this experiment.

Participants in both groups completed the training procedures two times per week (on different days) for four weeks, for a total of eight completed sessions. Participants were informed that they would be randomly assigned to one of two attention training groups. The protocol was described to the participants by the clinician administering the interview as an experimental procedure to determine the efficacy of a computer treatment for anxiety. Participants were informed that, depending on their random group assignment, the computer program they would complete could be either a placebo condition that was not designed to influence their anxiety or an experimental treatment condition that was designed to reduce their anxiety. This protocol was approved by the university's Institutional Review Board (IRB)

V. RESULTS

This section is related to the presentation of the study results. Both of the proposed algorithms were evaluated by calculating EER values. The estimation method was the same for both the paired comparison and combined data algorithms and consisted of the stages presented further.

Firstly, we had chosen 27 classes, which consisted of 10 and more datasets, out of the whole number of classes equaled 45. Then for each chosen class, we alternately selected one dataset
from this class and all datasets from all the other classes for testing. Other datasets of the class were used for forming a template of the class. After the test, the falsely rejected datasets and falsely accepted datasets were determined for various thresholds. This operation was repeated for each dataset of each chosen class. At the end, based on the collected statistics, ROC curves were plotted (Fig. 11) for both algorithms, and EER for the algorithm was calculated at such a threshold value, where FRR was equal to FAR.

The results of the evaluation were comparable for both of the proposed algorithms. At first, we applied the paired comparison algorithm. EER for this algorithm does not exceed 15.44 %. Then we assessed the combined data algorithm. The EER value does not exceed 16.18 %. Hence, we can state that both algorithms showed good results for the data obtained with a low-frequency eye tracker.

TABLE IV

Raw Data Samples Obtained for a Particular Person During Experimental Study

RecordingTimestamp	GazeEventType	GazePoint (X,Y)		EyePosition (X,Y,Z) Left/Right			PupilSize Left/Right
...	...	...	...	...	...	...	...
1133	Fixation	96.55	162.64	123.56 181.55	179.35 181.46	578.90 576.15	4.04 3.89
1168	Fixation	98.05	166.25	123.54 181.52	179.37 181.48	578.86 576.19	3.97 3.81
1202	Saccade	98.03	153.73	123.54 181.52	179.36 181.46	578.86 576.17	3.90 3.86
1235	Saccade	96.78	167.08	123.49 181.47	179.44 181.54	578.98 576.19	3.86 3.70
1269	Fixation	95.12	162.65	123.45 181.44	179.42 181.59	578.85 576.21	3.82 3.73
1301	Fixation	97.89	165.48	123.40 181.35	179.40 181.57	578.89 576.18	3.84 3.64
1337	Fixation	95.45	163.26	123.33 181.31	179.42 181.59	579.00 576.22	3.75 3.60
1368	Fixation	96.20	167.56	123.26 181.22	179.40 181.61	578.85 576.15	3.78 3.59
1401	Saccade	133.63	161.10	123.65 181.62	179.36 181.63	578.80 576.25	3.79 3.56
1433	Fixation	135.83	157.86	123.60 181.56	179.37 181.62	578.72 575.99	3.80 3.56
1467	Fixation	133.77	160.17	123.56 181.54	179.35 181.62	578.62 575.91	3.81 3.56
...	...	...	...	...	...	...	...

TABLE V

Amount of Experiments Taken By Participants

Amount of tests	Percent of participants
12	2.2
10	57.8
9	4.4
7	2.2
6 or less	33.3

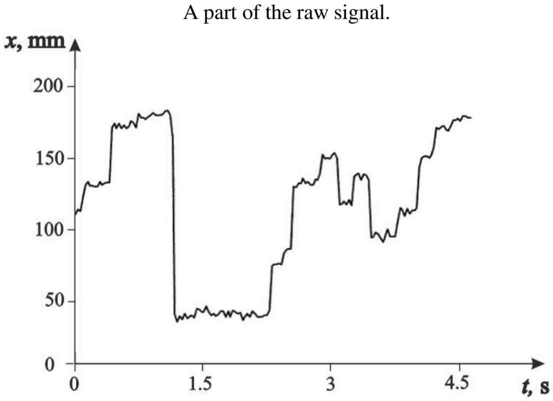
VI. Discussion of the Results

This section sums up all the obtained results. As presented in the approach description, we had proposed two algorithms based on different classifiers to be used for the identification purpose. List of the considered eye movements' features is the same in both algorithms and, as described in previous sections, consists of four coordinate points, the first order difference for three coordinate points, the second order difference for two points, one third order difference.

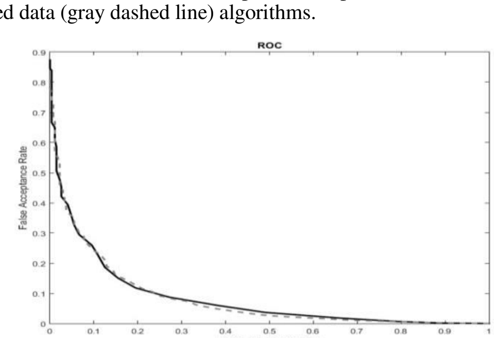
The first algorithm, i.e. the paired comparison algorithm, is based on k-Nearest Neighbors classification method. The calculated equal error rate does not exceed 15.44 %. The second algorithm is based on Naïve Bayes classification method. The evaluation scheme for this algorithm was similar to the kNN-based one, and the obtained EER does not exceed 16.18 %.

To sum up, comparison of the evaluation results for both of the proposed algorithms had shown that they are almost

A part of the raw signal.



ROC curves for the evaluation of the paired comparison (black solid line) and combined data (gray dashed line) algorithms.



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comparable between each other. Although, the lowest error rate for the paired comparison algorithm does not exceed 15.44 %, combined data algorithm requires less number of operations to make final decision.

It should be mentioned that in real information systems it will take a great amount of time and server resources to check all the database, while performing identification procedure. In order to reduce time spent on the calculation stages, our approach can be extended by adding physiological feature named pupil distance. This feature describes the distance between eye pupils and is stationary for each person, though it can not be used as one of the basic eye movements features due to the proximity of values for different people. However, it can be applied as a condition parameter in order to reduce a number of classes a dataset might be related to. Eye tracker provides information about an eye position in a specified $A^0x^0y^0z^0$ coordinate system, where A^0z^0 axis is used to compute the distance from the eye tracker to person's eyes. Hence, calculation of the distance between the eye pupils can be made by the following algebraic expression:

$$\sqrt{(x_L^0 - x_R^0)^2 + (y_L^0 - y_R^0)^2 + (z_L^0 - z_R^0)^2}, \qquad (11)$$

where (x_L^0, y_L^0, z_L^0) and (x_R^0, y_R^0, z_R^0) are coordinates of the left and the right eye pupil in $A^0x^0y^0z^0$ coordinate system.

In our work, we consider application of the low-frequency eye tracker for collecting necessary eye tracking data. As described in previous sections, most of the authors eval-uated their algorithms on eye movements' data collected by high-frequency devices, e.g. 120-400 Hz eye trackers or high quality cameras. Comparing the results obtained by our algo-rithms to the results from one of the observed sources [18], we can state that the performance of our algorithm with 15.44 % EER for the paired comparison algorithm is corresponding with the different algorithm, where authors obtained HTER equaled 13.1 %, though they were using a 500 fps camera to collect eye tracking data. Hence, the proposed approach shows significant results for low-frequency eye trackers, and states that such devices can be applied for the identification purpose.

It is important to reveal a possible cause of errors that can be obtained during the algorithm's evaluation. As for the applied algorithms, as mentioned above, error can be caused by:

- Limiting number of terms in Taylor's series due to the device's capabilities
- A possible error when applying approximation by the finite differences method
- A standard device error (as for eye tracker, e.g. measure-ments' latency, low or extremely high illumination, etc.)

Measure of Attention Bias

Our first goal was to demonstrate change in bias from pre-training to post-training in the AMP group using the novel words from the test set. These data are summarized in

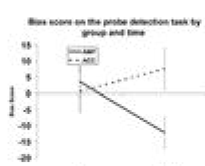
Table 2

Means and standard deviations of response latencies by group on the probe detection task

	AMP M (SD)		ACC M (SD)	
	Pre-training	Post-training	Pre-training	Post-training
Probe position				
Top				
Threat word				
Top	589 (175)	526 (100)	635 (206)	543 (115)
Bottom	593 (179)	510 (89)	641 (214)	553 (135)
Bottom				
Threat				

Means and standard deviations of response latencies by group on the probe detection task

We calculated bias scores as per MacLeod et al. (1988); these data are depicted in Figure 1. We submitted participants' bias scores for words in the test set to a 2 (Group: AMP, ACC) × 2 (Time: pre-training, post-training) ANOVA with repeated measures on the second factor. The main effects of Group, $F(1, 27) = 1.53$, $p = .22$, and Time, $F(1, 27) = 0.80$, $p = .39$, were not significant. However, there was a significant interaction of Group × Time, $F(1, 27) = 5.40$, $p < .03$. To follow up this interaction we conducted simple effects analyses. Simple effect of Time revealed that the participants in the AMP group showed a reduction in their attention bias from pre-training to post-training, $t(13) = 3.21$, $p \times .007$, d = 3.3 while those in the ACC group did not, $t(14) = -.84$, $p = .41$, d = -1.0. Simple effect of Group revealed that groups did not differ in their bias score at pre-training, $t(27) = 0.46$, $p = .65$. However the AMP group showed significantly lower bias scores than the ACC group at post-training, $t(27) = 2.18$, $p < .05$.



Change in attention bias

Measures of Anxiety and Depression

We submitted participants' scores on self-report and interviewer measures to separate 2 (Group: AMP, ACC) × 2 (Time: pre-training, post-training) ANOVAs with repeated measurement on the second factor. These analyses are summarized in With the exception of the HAMD and the PSWQ, all interactions of Group × Time were significant (*p*s<.05).

Table 3

Means and standard deviations for self-report and interviewer measures

	AMP		ACC		Results		
	Pre	Post	Pre	Post	Group	Time	Group × Time
	M (SD)	M (SD)	M (SD)	M (SD)	F (p)	F (p)	F (p)
STAI-T	60.9	47.3	58.6	55.6	0.72	26.72	10.84
	(8.9)	(10.4)	(10.2)	(12.3)	(0.4)	(0.00)	(0.003)
STAI-S	59.1	41.4	51.1	49.8	0.00	11.81	8.87
	(10.5)	(8.9)	(9.8)	(13.7)	(0.9)	(0.002)	(0.006)
[illegible]	24.6	14.5	22.8	22.1	0.70	7.17	5.50

Means and standard deviations for self-report and interviewer measures

To examine change in each we followed significant interactions with paired t-tests. For self-report measures, these analyses revealed that participants in the AMP group showed a significant decrease in their scores from pre-training to post-training on the STAT-T, t (13) = 4.76, p < .001, d= 1.40, STAI-S, t (13) = 4.27, p < .001, d = 1.81, BDI, t (13) = 2.69, p < .02, d= 0.90, and WDQ, t (13) = 4.30, p < .001, d= 1.14. The same paired t-tests in the ACC group did not reveal significant changes on the STAI-T, t (14) = 1.89, p < .08, d = 0.27, STAI-S, t (14) = 0.35, p < .74, d = .11, BDI, t (14) = 0.40,p < .70, d = .07, or WDQ, t (14) = 1.35, p < .20, d = 0.36. Similar analyses on the interviewer administered measures revealed that the AMP group showed a significant decrease in their scores on the HRSA, t (13) = 4.27, p < .001, d = 1.36. In contrast, the ACC group did not show a significant changed in their HRSA scores, t (14) = 1.47, p < .16, d = 0.31.

We also examined the number of participants who no longer met DSM-IV diagnosis for GAD at post treatment. These analyses revealed that a significantly larger proportion of the participants in the AMP group (50%) compared to the ACC group (13%) no longer met diagnostic criteria for GAD after training, $X^2(1) = 4.55$, $p < .03$.

Mediational Analyses

To test the hypothesis that the AMP exerted its influence on anxiety and depression through change in attention bias to threat, we conducted mediational analyses following the procedure described by MacKinnon and colleagues (MacKinnon, Fairchild, & Fritz, 2007; MacKinnon, Lockwood, Hoffman, West, & Sheets, 2002). In brief, this procedure tests the product of the coefficients for the effects of (1) the independent variable (Group: AMP, ACC) to the mediator (attention bias after training) (α), and (2) the mediator to the dependent variable (change in scores, HRSA, STAI-T, STAI-S, BDI, WDQ, from pre- to post-training) when the independent variable is taken into account (β). This procedure is a variation on the Sobel (1982) test that accounts for the non-normal distribution of the αβ path through the construction of asymmetric confidence intervals (MacKinnon, Fritz, Williams, & Lockwood, 2007). Our results indicated that the 95% confidence interval of the indirect path (αβ.) did not overlap with zero for change in anxiety for HRSA (lower limit = .015, upper limit = .343). The same indirect paths for all other measures (STAI-T, STAI-S, BDI, WDQ) overlapped with zero, indicating an absence of a significant mediation.

VI. CONCLUSION

Protection of the access to different information systems is widely discussed nowadays due to the fast growth of the Web and a number of systems needing to acquire such security feature. Biometric identification methods are becom-ing embedded in different systems and devices as they attempt to provide one of the most secure algorithms and could protect systems from being accessed by impostors. When eye tracking systems came into being and became accessible for the people, an idea of developing person identification methods based on the eye tracking data had been formed. Since then, many authors had provided the results of their works. However, most of the works consider application of high frequency devices used to collect eye tracking data. Hence, the main idea of our work was to develop approach and algorithms that could provide low error rate despite using a low-frequency eye tracker.

In our work, we present an approach, which is based on the saccades analysis. Each person has a unique saccade gaze pattern that could be mathematically described by computing specific features of the eye movements. Our approach is based on calculation of these features of the eye movements and applying classification algorithms to the formed data. We consider two algorithms: paired comparison and combined data algorithms. Experimental results had shown that the lowest error rate was obtained for the paired comparison algorithm and equaled 15.44 %, though results for the com-bined data algorithm were approximately comparable with 16.18 %. Hence, our approach provides high accuracy for the eye tracking data collected with a low-frequency eye tracker and, therefore, it can be applied in real systems for person identification. Our results suggest that the translation of basic psychopathology research to address a clinical condition may prove useful in developing new interventions. Moreover, these interventions may help identify the mechanisms that are involved in the pathogenesis of psychiatric conditions. Future studies should examine the additive and/or interactive effects of attention training and traditional interventions (i.e., medication and CBT), as well as the combination of other types of information processing training (e.g., interpretation modification).

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