Biometric Authentication via Anatomical Characteristics of the Oculomotor Plant

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Abstract

A novel biometrics approach that performs authentication based on the anatomical characteristics of the oculomotor plant (comprising the eye globe, its muscles and the brain's control signals) is presented. The extraction of the oculomotor plant characteristics (OPC) is achieved by analyzing the recorded eye movement trajectories via a 2D linear homeomorphic mathematical representation of the oculomotor plant. The derived OPC allow authentication via various statistical methods and information fusion techniques. Authentication based on OPC yielded Half Total Error Rate of 25% for a pool of 59 recorded subjects, when the eye movement records were affected by the re-calibration biases of the eye tracking equipment. However, when the impact of re-calibration is removed the designed methods allow the achievement of an HTER close to 15% for the same pool of subjects. The OPC biometric authentication has high counterfeit resistance potential, because it includes both behavioral and physiological human attributes that are hard to reproduce.

1. Introduction

The methods of biometric identification have evolved throughout history from basic measurements of head dimensions [1] to more advanced techniques involving fingerprints [2], iris [3], and face recognition [4]. But the above-mentioned techniques are not completely fraud-proof since they are based on human body characteristics that can be replicated with modern technological advances [2-5]. As a result there is a significant need in biometrics research to identify methods that are highly counterfeit resistant. In this paper we present a method that has potential to be highly counterfeit resistant because it employs non-visible anatomical structures of the human eye.

The human eye already provides a plethora of information useful for biometrics. The physical and behavioral properties of the eye are employed in biometrics based on the iris [6], face recognition [4], retina [7], periocular information [8], recordings of the raw eye position, velocity signal and pupil dilation [9, 10].

In terms of its anatomical structure, the eye provides a unique opportunity for identification by containing a multitude of anatomical components that together comprise the so-called *Oculomotor Plant* (OP). These components are the eye globe and its surrounding tissues, ligaments, six extraocular muscles each containing thin and thick filaments, tendon-like components, various tissues and liquids [11]. The dynamic and static characteristics of the OP are represented by the eye globe's inertia, dependency of an individual muscle's force on its length and velocity of contraction, resistive properties of the eye globe, muscles and ligaments, frequency characteristics of the neuronal control signal sent by the brain to the extraocular muscle and the speed of propagation of this signal. Individual properties of the extraocular muscles vary depending on the role each muscle performs. There are two roles: the agonist - muscle contracts and pulls the eye globe in the required direction and the antagonist - muscle expands and resists the pull [12].

Numerically evaluating the OP characteristics (OPC) could yield a highly counterfeit resistant biometric method because OPC represent dynamic behavioral and physiological human attributes that only exist in a living individual. Biometric authentication via OPC promises to be highly repeatable because any type of random stimulus ideally would produce the same OPC values.

Accurate estimation of the OPC is challenging due to the secluded nature of the corresponding anatomical components, which necessitates indirect estimation and includes noises and inaccuracies associated with the eye tracking equipment, classification and filtering of the eye movement signal, mathematical representation of the OP, and actual algorithms for numerical estimation of OPC. This work addresses these challenges and presents methods that might eventually allow accurate authentication of an individual based on the anatomical characteristics of the OP using eye tracking technologies.

Closely related work. In general the OPC biometrics approach presented here is similar to the one presented by Komogortsev and colleagues [13] however this work advances the state of the art in OPC biometrics via following major contributions: a) ability to process two dimensional eye movements vs. one dimensional ones by the use of a linear 2D mathematical model of the human eye b) very thorough establishment of the baseline performance via use of more accurate/high sampling frequency eye tracking equipment and a large amount of recorded eye movements c) addition of eye movement data filtering methods to ensure high quality biometric data d) use of different probabilistic approaches for person authentication e) use of information fusion methods. Methods applied in this work could achieve FAR and FRR rate of 15% within each single recording session vs. FAR of 5.4% and FRR of 56.6% achieved by Komogortsev and colleagues within each single recording.

2. Biometric Authentication via Anatomical Characteristics of the Oculomotor Plant

2.1. Overview

Figure 1 presents an overview of the proposed method. The recorded eye movement signal from an individual is supplied to the <u>Eye Movement Classification</u> module that classifies the eye position signal into fixations (movements that keep an eye focused on a stationary object of interest) and saccades (extremely rapid eye rotations between the points of fixation). OPC can be extracted only from a dynamic eye movement such as saccade. Therefore, a sequence of classified saccades are sent to the second module labeled <u>Oculomotor Plant Mathematical Model (OPMM)</u>, which generates simulated saccades' trajectories based on the default OPC values that are grouped into a vector with the purpose of matching the simulated trajectories with the recorded ones. Each individual saccade is matched independently of any other saccade. Both recorded and simulated trajectories for each saccade are sent to the <u>Error Function</u> module where the error between the trajectories is computed. The error triggers the <u>OPC Estimation</u> module to optimize the values inside of the OPC vector and sends them to the OPMM to generate more accurate trajectories minimizing resulting error. After several iterations, when the minimum error is obtained, a sequence of the optimized OPC vectors is supplied to the <u>Information Fusion</u> and <u>Person Authentication</u> modules to authenticate a user. The Person Authentication module accepts or rejects a user based on the recommendation of a given classifier. The Information Fusion module aggregates information related to OPC vectors and works with the Person Authentication module to authenticate a person based on multiple classification sources.

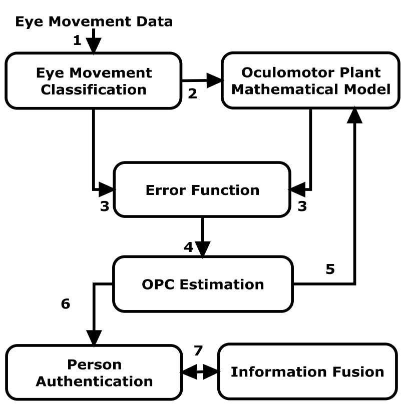

Figure 1. Biometrics via anatomical characteristics of the Oculomotor Plant.

2.2. Eye Movement Classification

An automated eye movement classification algorithm plays a crucial role in aiding the establishment of the invariant representation for the subsequent estimation of the OPC values. The goal of this algorithm is to automatically and reliably identify the beginning, end and all trajectory points from a very noisy and jittery eye movement signal. The additional goal of the eye movement classification algorithm is to provide additional filtering for saccades to ensure their high quality and a sufficient quantity of data for the estimation of the OPC values.

A standardized Velocity-Threshold (I-VT) algorithm [14] was selected due to its speed and robustness. A comparatively high classification threshold of 70°/s was employed to reduce the impact of trajectory noises at the beginning and the end of each saccade. Additional filtering discarded saccades with amplitudes of less than 5°, duration of less than 20 ms., and various trajectory artifacts that do not belong to normal saccades.

2.3. Oculomotor Plant Mathematical Model

The OPMM has to be able to quickly simulate accurate saccade trajectories while containing major anatomical components related to the OP.

The linear homeomorphic 2D OP mathematical model developed by Komogortsev and Jayarathna [15] was selected. This OPMM, driven by twelve differential equations, is capable of simulating saccades with properties resembling normal humans on a 2D plane (e.g. computer monitor) by considering physical properties of the eye globe and four extraocular muscles: medial, lateral, superior, and inferior recti.

The following advantages are associated with a selection of this OPMM: 1) major anatomical components are present and can be estimated, 2) linear representation simplifies the estimation process of the OPC while producing accurate simulation data within the spatial boundaries of a regular computer monitor, 3) the architecture of the model allows dividing it into two smaller models of the form that is described by Komogortsev and Khan [16]. One of the smaller models becomes responsible for the simulation of the horizontal component of movement and the other for the vertical. Such assignment, while producing identical simulation results when compared to the full model, allows a significant reduction in the complexity of the required solution and allows simultaneous simulation of both movement components on a multi-core system.

2.4. OPC vector

The following subset of nine OPC was selected as a vector to represent an individual saccade for each component of movement (horizontal and vertical): length tension - the relationship between the length of an extraocular muscle and the force it is capable of exerting, series elasticity - resistive properties of an eye muscle while the muscle is innervated by the neuronal control signal, passive viscosity of the eye globe, force velocity relationship - the relationship between the velocity of an extraocular muscle extension/contraction and the force it is capable of exerting - in the agonist muscle, force velocity relationship in the antagonist muscle, eye globe inertia, agonist and antagonist muscles' tension intercept that ensures an equilibrium state during an eye fixation at primary eye position, the agonist muscle's tension slope, and the antagonist muscle's tension slope. All tension characteristics are directly impacted by the neuronal control signal sent by the brain and therefore partially contain the neuronal control signal information.

If both horizontal and vertical components of a saccade are considered, the resulting OPC vector would contain eighteen unique OPC.

2.5. Error Function

The goal of the Error Function module is to provide high sensitivity to any differences between the recorded and simulated saccade trajectories.

The error function was implemented as the absolute difference between the saccades that are recorded by an eye tracker and saccades that are simulated by the OPMM.

$$R = \sum_{i=1}^{n} |t_i - s_i| \quad \textbf{(1)}$$

where n is the number of points in a trajectory, t_i is a point in a recorded trajectory and s_i is a corresponding point in a simulated trajectory. The absolute difference approach provides an advantage over other estimations such as RMSE due to its higher absolute sensitivity to the differences between the trajectories.

2.6. OPC Estimation

The goal of the OPC estimation module is to provide a mechanism for optimizing the values in the OPC vector to ensure a minimum error between the simulated and recorded saccadic trajectories.

The Nelder-Mead (NM) simplex algorithm [17] (fminsearch implementation in MATLAB) is used in a form that allowed simultaneous estimation of all OPC vector parameters at the same time. A lower boundary was imposed to prevent reduction of each individual OPC value to less than 10% of its default value. Stability degradation of the numerical solution for differential equations describing the OPMM served as an upper boundary indicator for each OPC parameter.

2.7. Person Authentication

The goal of the Person Authentication module is to confirm or reject claimed identity based on the comparison of the two sets of OPC vectors.

One of the biggest challenges associated with the OPC biometrics is the amount of variability present in the estimated OPC. Experiments from which one might infer the variability of OPC values are almost non-existent in the OP literature. Usually, average numbers are derived from strabismus surgeries performed on a limited number of patients [18], and even from cat studies [19]. As a result it is hard to estimate a priori the amount of variability of the values for the OP properties in a large pool of normal humans. We hypothesize that a substantial amount of variability is present in the OPC to ensure accurate authentication. Therefore, authentication methods that allow addressing variability concerns are required to make OPC biometrics successful.

Two classifiers fit this purpose: a) two-sample Student's *t*-test [20] enhanced by voting and b) Hoteling's T-square test [21]. Both methods are able to perform acceptance and rejection tests. In the acceptance test, two datasets belonging to the same individual are compared. In the rejection test, the datasets are taken from different people. The outcome of each test determines the authentication accuracy of the corresponding authentication approach.

2.7.1 Student's t-test with Voting

The following Null Hypothesis (H_0) is formulated as a part of the Student's t-test given that two sets of OPC vectors, one from the user i and the other from the user j, are compared: "H_0:There is no difference between the OPC's estimation sequences from the users i and j". In order to make a conclusion about the difference between two users, the statistical significance (P_{level}) resulting from the test is compared to the significance threshold α. If the resulting P_{level} is smaller than α, the H_0 is rejected indicating that the OPC estimation belongs to different people. Otherwise, the H_0 is accepted indicating that the OPC estimation belongs to the same person.

The Student's t-test approach allows performing an authentication based on just a single OPC, therefore not taking immediate advantage of the potential information included in other OPC. In this work we enhance the Student's t-test by considering voting methods described by Lam and Suen [22]. Such method accepts a person assuming that for at least k OPC the H_0 is accepted and rejects a person if H_0 is accepted for less than k OPC. The performance of the Student's t-test with voting is affected by the significance threshold and number of votes k.

2.7.2 Hoteling's T-square Test

Hoteling's T-square test [21] is a multivariate representation of the Student's t-test and therefore provides an opportunity to assess the similarity of the multivariate distribution for the entire OPC vector instead of just single parameter as it was done in the Student's t-test. The performance of the Hoteling's T-square test is only affected by the value of significance threshold.

2.8. Information Fusion

Information fusion techniques allow improvement of the overall accuracy of an authentication method by considering the information from multiple classifiers [23]. Fusion techniques are usually broken into two categories: a) fusion prior to matching and b) fusion after matching. Fusion prior to matching consolidates information for classifiers prior to the identity match. Fusion after matching consolidates classification results when identity decision is already made by each classifier. Both types of fusion are employed in our work to increase the accuracy of the OPC-based authentication.

2.8.1 Fusion Prior to Matching

Our fusion approach fuses OPC vectors estimated from horizontal and vertical movements taking advantage of the two dimensional Oculomotor plant model, effectively doubling the number of OPC parameters in the combined OPC vector. We call this type of fusion horizontal fusion

2.8.2 Fusion After Matching

In the fusion after matching category we consider a decision level fusion technique proposed by Daugman in a form of AND/OR approach [22]. For simplicity we call this method *logical fusion*. The AND method only accepts an individual if all of the classifiers accept the individual, therefore providing an opportunity to reduce the combined false acceptance rate and increase the resulting false rejection rate. The OR method only accepts an individual if one of the classifiers accepts such individual therefore providing an opportunity to increase the combined false acceptance rate and decrease the combined false rejection rate.

3. Methodology

3.1. Apparatus & Software

The data was recorded using the EyeLink II eye tracker with a sampling frequency of 1000Hz [24]. The EyeLink II provides drift free eye tracking with a spatial resolution of 0.01º, and 0.25-0.5º of positional accuracy. EyeLink II enables eye to camera distances between 60 and 150cm and horizontal and vertical operating range of 55° and 45° respectively. To ensure high accuracy of the eye movement recording a chin rest was employed. The chin rest was positioned to assure 70cm distance between the display surface and the eyes of the subject.

The OPC biometrics architecture was implemented in MATLAB. All data was processed offline.

3.1. Participants

A total of 59 participants (46 males/13 females), ages 18 – 45 years with an average age of 24 (SD=6.1), volunteered for the project. Mean positional accuracy of the recordings averaged between all screen regions was 1.41º (SD=1.91º).

All subjects participated in the two recording sessions that presented identical eye movement invocation tasks with approximately a 20 minute break between the sessions. Before each recording session, for each subject and eye movement invocation task, the eye tracking equipment was recalibrated to ensure high positional accuracy of the recorded data.

3.2. Stimuli & Resulting Datasets

The goal of the stimulus was to invoke a large number of vertical and horizontal saccades to allow reliable authentication. The stimulus was displayed as a jumping dot, consisting of a grey disc sized approximately 1º with a small black point in the center. The dot performed 100 jumps horizontally and 100 jumps vertically.

The amplitude of the vertical jumps was 20º for all subjects. However, horizontal jumps had the amplitude of 20º for approximately half of the subjects (27) and 30º for another half (32). The variation in the horizontal amplitudes allowed assessing classification performance due to stimulus changes while fixed vertical amplitude allowed testing for the scalability of the OPC biometrics for a larger pool of individuals.

The horizontal component of movement from horizontal saccades with 20º amplitude and the vertical component of movement from the vertical saccades with 20º amplitude obtained from first 27 subjects comprised Dataset I. The horizontal component of movement from horizontal saccades with 30º amplitude and the vertical component of movement from the vertical saccades with 20º amplitude recorded from the remaining 32 subjects comprised Dataset II. Dataset I+II combined data from datasets I and II.

The use of just horizontal movement components from purely horizontal saccades and vertical component from purely vertical saccades allows substantial improvement of the quality of data employed for authentication by disregarding orthogonal movement jitter. Additionally, such eye movement data allows a subsequent check for saccade normality by filtering via the corresponding amplitude- duration and amplitude- maximum velocity relationships (main-sequence relationship) [12] and discard outliers.

Each dataset represents the data from the first and second recording sessions for all subjects. Each subject in a dataset is represented by 30 "best" saccades in cases when only one movement component is considered and 60 in cases when both horizontal and vertical movement components are considered. Best saccades are defined as the saccades that produce the smallest error between the recorded and the

Method & Data Description	Dataset	I			II			I+II		
	Session	1	2	1+2	1	2	1+2	1	2	1+2
1	T(hor)	29	24.5	34	25.5	35	36.5	23	25.5	32
2	T(ver)	35	33	36.5	30	42.5	35.5	33	36	34
3	S(hor)	22	29.5	38.5	31	33	37	25	29	35.5
4	S(ver)	22	29.5	36	44	43.5	40	38.5	37	36
5	T(hor,ver)	32.5	18.5	25	22.5	36	35	25	26.5	29.5
6	S(hor,ver)	24	30.5	31.5	30.5	33.5	33.5	22.5	26.5	32
7	T(hor) *OR* S(hor)	29.5	28.5	31	28.5	35.5	33	24	27.5	31.5
8	T(ver) *OR* S(ver)	36.5	33	33.5	33.5	42.5	35.5	50	50	33.5
9	T(hor) *OR* T(ver)	23.5	32.5	31.5	31.5	34	36.5	27	33.5	32
10	S(hor) *OR* S(ver)	24.5	33	33	39	41	39	29	36.5	33.5
11	T(hor) *AND* S(hor)	28.5	23	33	28.5	35	33.5	24.5	25.5	30
12	T(ver) *AND* S(ver)	34	33	32.5	34.5	45	34	32.5	37	32
13	T(hor) *AND* T(ver)	32	21	35	29.5	40.5	38.5	28.5	28.5	35
14	S(hor) *AND* S(ver)	28.5	23	28.5	30.5	31.5	42.5	24	27	33.5
15	T(hor,ver) AND S(hor,ver)	24	24	35	22.5	37.5	35.5	25.5	27	34
16	T(hor,ver) OR S(hor,ver)	24	26	37.5	24.5	33.5	41	21.5	23.5	38

Table I. Performance of the OPC biometrics for various authentication methods and datasets expressed in the HTER (numbers show percentages). In the Methods & Data Description column T represents Hoteling's T-square test and S represents Students t-test with voting. (hor) represents data from horizontal movement component of horizontal saccades, (ver) represents data from vertical movement of vertical saccades, (hor,ver) represents the case of horizontal data fusion. OR and AND represent logical fusion techniques. Dataset row indicates datasets described in Section 3.2 and Dataset I+II combines subjects' records from Datasets I and II. Session row represents recording session data (Section 3.1), i.e. 1 indicates that first half of the saccades from session 1 was employed for the enrollment and the other half was employed for the authentication and 1+2 indicates that the saccades from session 1 were employed for the enrollment and saccades from session 2 were employed for the authentication and vice versa. Note that results related to Students t-test with voting represent values obtained with 4 votes (8 votes in case of horizontal fusion). Significance threshold α for Students t-test and Hoteling's T-square test was 0.1

stimulated trajectory. Such filtering enables further improvement of the quality of the data employed for the authentication.

3.3. Performance evaluation metrics

The following metrics were employed to assess authentication accuracy:

False Acceptance Rate (FAR) – expresses, in general, the probability that a given individual is falsely accepted into the system. This rate was computed as the number of rejection tests that failed (marking two different subjects as same person) divided by the total number of rejection tests performed.

False Rejection Rate (FRR) – expresses, in general, the probability that a given individual is falsely rejected from the system while it should be accepted. In this work, the FRR was computed as the number of acceptance tests that failed (marking two datasets from the same person as being from different people) divided by the total number of acceptance tests performed.

Half total error rate (HTER) is defined as the averaged combination of false acceptance and false rejection rates.

4. Results

Principal component analysis (PCA) was performed on nine OPC that comprise an OPC vector in an effort to reduce the number of parameters needed for the authentication. Results of PCA indicate that series elasticity, passive viscosity of the eye globe, eye globe's inertia, agonist muscle's tension slope, and the antagonist muscle's tension slope account for 77% of total variance in the recorded data. Only authentication results involving these six OPC for each of the movement component are presented further by Table I.

4.1. Equipment Calibration Impact

Saccades employed from the same recording session for enrollment and authentication frequently resulted in the smaller HTER than in cases when saccades from one session were used for the enrollment and from another for the authentication. For example for the T(hor) method, Dataset I+II, single session HTER are 23-25.5%, while combined session increased HTER to 32%. We hypothesize that such differences might have occurred due to biases introduced by the calibration procedure and can be explained by mathematics employed in Eye Link eye tracker for calibration and subsequent interpolation of the eye gaze coordinates.

During data collection all experimental parameters including the subject's head and equipment placement were carefully controlled by using a chinrest with a goal of keeping them exactly the same between the recording sessions. However, the results of the calibration procedure which matches eye gaze vector with screen coordinates performed by the Eye Link eye tracker were different for each recording session for the same subject, within specified positional accuracy error. This phenomenon can possibly be explained by the calibration algorithms employed by the Eye Link eye tracker. The Eye Link system uses algorithms similar to Stampe's [25], which employs 2D regression-based gaze interpolation between the calibration points. Stampe's algorithms do not guarantee head pose invariance. As a result the interpolation is extremely sensitive to even slight differences in estimation of the eye-gaze direction for any point (especially in periphery) in the calibration map and even the slightest changes in subject's head position are translated into substantial calibration biases present in the recorded data. We hypothesize that the application of the 3D model-based eye-gaze estimation [26] as a part of the calibration and eye gaze components might prove beneficial for the OPC biometrics due to higher head pose invariance. However very high-sampling frequency commercial eye-tracking systems that use such type of gaze estimation are not available yet.

4.2. Impact of Person Authentication Methods

As shown in rows 1-4 in Table I, Hoteling's T-square test in general produced slightly more accurate authentication results than Student's t-test with voting for all datasets under consideration. For example, in Dataset I+II, the Hoteling's T square test produced HTER of 32% for horizontal while Student's t-test with voting produced HTER of 35.5%.

4.3. Impact of 2D Eye Movements & Horizontal Fusion

In rows 7-8 of Table I, the consideration of both the vertical and horizontal components of the eye movements via horizontal and vertical fusion ensured slightly more accurate authentication. This trend was true for both Hoteling's T-square test and Student's t-test with voting. For example in Dataset I+II the results of the Hoteling's T square test produced HTER of 32% for horizontal and 34% for vertical data; however, the use of vertical and horizontal components of movement via horizontal fusion reduced HTER to 29.5%.

4.4. Impact of Logical Fusion

According to rows 7-14 in Table I, application of logical fusion provided a slight increase in the authentication accuracy when compared to pure person authentication methods. For example, in Dataset I+II, Hoteling's T square test for the horizontal component produced HTER of 32% and Student's t-test with voting produced HTER of 35.5%; however, logical fusion reduced the HTER to 30% (row 11).

Logical fusion did not always provide the improvement in accuracy when compared to horizontal/vertical fusion. For example, in Dataset I+II, Hoteling's T square test with horizontal fusion yielded HTER of 29.5% and all logical fusion methods provided HTER that was slightly higher.

Approaches that involved both logical and horizontal and vertical fusion

4.5. Impact of Stimuli Properties

The results from horizontal data presented in row 1 and 3 of Table I did not indicate large changes when different amplitude of step stimulus was presented. The corresponding HTERs were 4-16.5% smaller within each single session than between sessions for the group of subjects with presented stimulus amplitude of 30° and the group of subjects presented with stimulus amplitude of 20°. Multiple session results differed slightly by <2%.

For the Dataset I+II, where different stimulus amplitudes were used for different subject groups, the accuracy of authentication was improved by 1-4.5%. This result suggests that stimulus amplitude does impact the results of biometric authentication, however slightly. Additional research is required for additional clarification.

4.6. Scalability of the OPC biometrics

The results from the vertical data presented in row 2 and 4 of the Table I indicate the scalability potential of the OPC biometrics, because horizontal component of movements considers saccades of the same amplitude. When the amount of subjects was increased from 27 to 59 the results of the authentication did not change significantly. The corresponding HTER remained almost the same for both Students t-test and Hoteling's T-square test. Multiple session results also were affected very slightly with accuracy decreasing by 1.5-4.5% in terms of HTER for both authentication methods for the larger group of subjects.

4.7. Receiver Operating Characteristics Curve

Figure 2 presents a Receiver Operating Characteristics (ROC) curve. The results include a mix of best performing methods with and without fusion according to the corresponding HTER for the data from Table I.

5. Limitations

Recording Equipment: The OPC biometrics exploration done in this work was conducted on very accurate eye tracking equipment with a very high sampling rate. Subjects were positioned in a chinrest to avoid potential accuracy issues. Additional research is required to understand the tradeoffs between the authentication accuracy of the OPC biometrics and equipment's sampling rate, positional accuracy, and freedom of head movements.

Calibration: The results indicate that there is a large impact of calibration methods on the resulting accuracy of authentication, necessitating further investigation into making OPC biometrics components less dependent on the calibration or/and employing eye tracking calibration techniques that maintain calibration consistency between the recording sessions.

Stimulus: The jumping dot stimulus employed in this

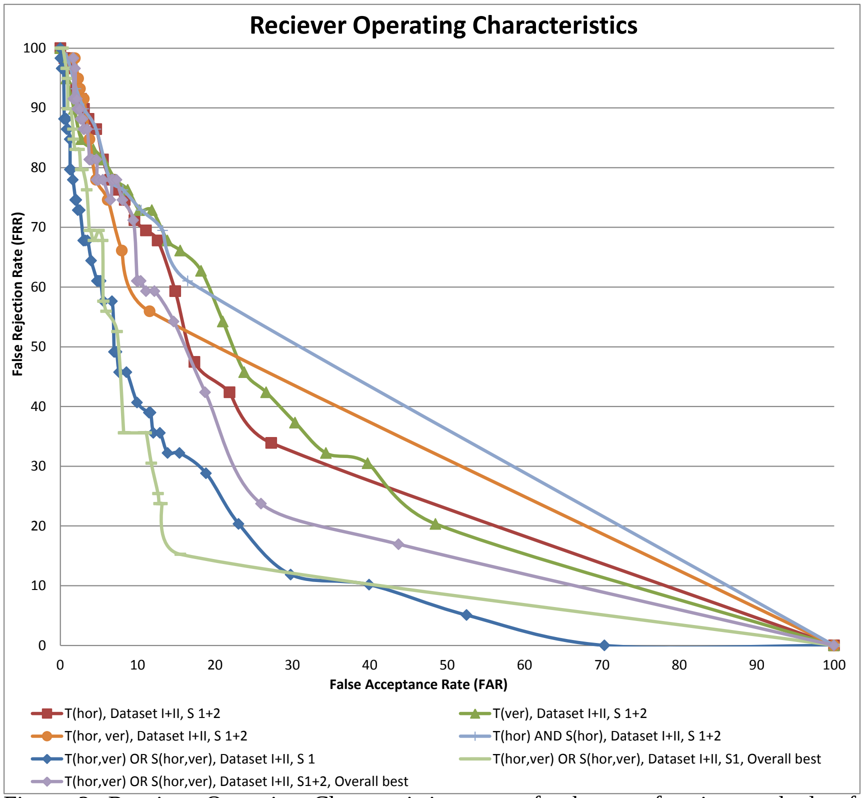

Figure 2. Receiver Operating Characteristic curves for best performing methods of biometric authentication via OPC. Biometric methods and datasets are coded similar to the data presented in Table I.

work was purposefully fixed in amplitude and exhibited a large number of jumps. Such fixed experimental parameters allowed us to establish a baseline for the OPC biometric performance in an environment that is close to ideal. However, additional work is required to understand the OPC biometric performance for saccades that have randomized amplitudes, various spatial placement, and different quantities.

OPC Estimation Speed: The estimation of an optimal OPC vector containing nine parameters from a single saccade takes on average two hours on an Intel Q6600 processor, using one core and assuming MATLAB implementation of the *fminsearch* function. However, the OPC biometrics architecture is highly parallelizable, with each individual saccade trajectory easily processed by a separate core. Additionally, implementation in a programming language such as C/C++ might speed up the estimation process.

The linear design of the OPMM makes it possible to seek analytical solutions to the differential equations describing the model, therefore providing an opportunity for the direct extraction of the OPC from saccade trajectories. However the search for such a solution presents a substantial analytical challenge and will be explored in future work.

Stability of the OPC trait: The time interval between the recording sessions for each subject was approximately 20 min. Such a time difference provides extremely limited insight in terms of the stability of the OPC biometrics over a longer time span and impact of such factors as stress, fatigue, aging and illness. Additional research needs to be conducted to explore the long term stability of the OPC trait.

6. Discussion

Highest Possible Accuracy between Multiple Sessions: It is possible to perform an authentication selecting "best" combination of OPC for each dataset, session set, and authentication method. These best combinations, in the multiple session categories, allow reducing the HTER by 4-9% compared to the results presented by Table II. The best combination of OPC parameters for Dataset I+II, Session 1+2 with a single authentication method provided the HTER of 29% in case of S(hor) method. The best overall result in the Database I+II, Session 1+2 aided by horizontal and logical fusion was produced by T(hor,ver) OR S(hor,ver) method with HTER of 25% (FAR=25%, FRR=25%). The ROC curve for the best performing method is displayed by Figure 2.

Highest Possible Accuracy within Single Sessions: The best combination of OPC parameters for Dataset I+II within a single session and a single authentication method achieved the HTER of 16.5% (FAR=16% and FRR=17%) for T(hor) method during Session 1. Overall best performance in the Database I+II, Session 1+2 aided by horizontal and logical fusion was produced by T(hor,ver) OR S(hor,ver) method with HTER of 15% (FAR=15%, FRR=15%). The ROC curve for the best performing method is displayed by Figure 2.

Large difference in the performance in cases when saccades from different and the same session (HTER=25% vs. HTER=15%) are employed for the enrollment and verification again support the hypothesis that eye tracker calibration methods might be responsible for such differences. Future investigation that involves eye tracking equipment with different calibration methods is required.

7. Conclusion and Future Work

This paper outlined and explored a novel biometrics approach that allows person identification via anatomical characteristics of the Oculomotor Plant (OP). Given the limited pool of 59 volunteers, the OPC biometrics in the authentication mode achieved the HTER of 25% in the optimal set of the OPC parameters and when eye movement records were affected by the eye tracking equipment calibration biases. When the impact of the calibration procedure was removed the resulting HTER was 15% in the best case.

Among statistical methods employed for person authentication Hoteling's T-square test in general provided higher accuracy. Information fusion prior to matching, combining horizontal and vertical components, achieved slightly higher authentication accuracy than when no fusion was performed. The same was true for the logical fusion methods employed after the initial match was done by a separate person authentication method. Application of both information fusion types at the same time, in general, did not provide higher authentication accuracy than employment of a single type of a fusion method. An increase in the number of subjects from 27 to 59 did not decrease the authentication performance. The assignment of different stimuli amplitudes to different subject groups very slightly improved authentication accuracy.

It is important to conduct more work to ensure OPC biometrics independence from equipment calibration biases, because this is the main factor degrading authentication performance. Additional work should be performed to allow faster estimation of the OPC values. The stability of biometrics needs to be verified against a more diverse array of stimuli, eye tracking equipment, larger group of subjects and a longer time span.

8. Acknowledgements

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