Biometric Identification based on the
Eye Movements and Graph Matching Techniques

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Abstract

The last few years a growing research interest has aroused in the field of biometrics, concerning the use of brain dependent characteristics generally known as behavioral features. Human eyes, often referred as the gates to the soul, can possibly comprise a rich source of idiosyncratic information which may be used for the recognition of an individual’s identity. In this paper an innovative experiment and a novel processing approach for the human eye movements is implemented, ultimately aiming at the biometric segregation of individual persons. In our experiment, the subjects observe face images while their eye movements are being monitored, providing information about each participant’s attention spots. The implemented method treats eye trajectories as 2-D distributions of points on the image plane. The efficiency of graph objects in the representation of structural information motivated us on the utilization of a non-parametric multivariate graph-based measure for the comparison of eye movement signals, yielding promising results at the task of identification according to behavioral characteristics of an individual.

Keywords: behavioral biometrics, eye movements, face perception, minimum spanning tree, Wald-Wolfowitz test
1. Introduction

Biometric identification has been a research field that since its introduction has undergone a
continuous evolution reflecting the technological developments of each era. Starting with the written
signature and the classic fingerprints, the biometric identification technology advanced to newer and
more delicate approaches such as iris recognition and face identification, methods that rely on the
physical characteristics of a person. The last few years however, a new trend arises on the biometric
identification research domain, concerning the exploration of new dynamical characteristics which are
capable of exploiting information directly originating from human brain’s activity. These types of
characteristics are generally known as behavioral features, with their major representatives being
keystroke dynamics, gait, speech and most recently eye movement features and characteristics based
on EEG signals (a thorough survey presented in Goudelis et al., 2009). The most promising among
the advantages offered by the employment of behavioral characteristics is the inherent difficulty of
forging them. The human brain activity exploration conducted in the scientific areas of
neurophysiology and neuropsychology, has lately produced some exceptional findings, mainly due to
the latest technological advances in EEG and fMRI techniques. The human brain mechanisms
involved in the formation of behavioral characteristics are so complicated however, that the
possibility of exactly modeling them in the near future seems unlikely.

The scanning sequence of eyes in a visual environment is considered to provide relevant
behavioral information about a person. Eye movements and their functionality in visual processing
procedures, had already caught a few researchers attention since the early half of the previous
century. Among the pioneers of vision research were M.A. Tinker (Tinker, 1946) and A.L. Yarbus
(Yarbus, 1967) who developed primitive tools of eye movement monitoring and conducted the first
studies involving the visual system and human eye movement principals. Noton and Stark (1971a,
1971b) stepped further, establishing the idea that certain scanpaths are formed by human eye
movements during the observation of visual stimuli. These studies provided strong evidence that the
underlying cognitive procedures, reflected in the movement of the eyes could possibly provide some
idiosyncratic information about a person. The following years researchers conducted various studies
inspecting eye movements while performing cognitive loading tasks. Examples include the
exploration of eye movements during the observation of web pages (Josephson and Holmes, 2002),
and eye movement based frameworks for image retrieval and categorization (Hardoon and Pasupa,
2010), (Oyekoya and Stentiford, 2007).

With our current work we aspire on extending the research domain involving eye movements
utilization for the purpose of biometric identification, originally suggested by Kasprowski and Ober
(2004). Our contribution is two-fold. On the first hand, an innovative visual target is proposed,
consisting of images that depict real human faces, which should facilitate the extraction of
idiosyncratic patterns from every subject. Secondly, a graph-theoretic framework is used for the first
time in order to process and compare the eye movement patterns, with the final goal of separating
subjects according to their biometrical characteristics.

Considering the high demanding scenarios that arise in modern era, eye movements provide
certain attractive advantages that argue in favor of their utilization in biometrics. Contactless
acquisition of the features is a frequently desired requirement for the implementation of flexible
biometric systems embedded in dynamical open environments. Latest technology eye tracking devices
may require no contact at all, making thus possible the remote monitoring of human eye movements.
An eye movement based biometric system can furthermore record the gaze of an individual during the
observation of some optical stimuli, e.g. an airport matrix or the poster of a face, with the recording
not being perceptible. Biometric features based on eye movements are capable in other words to
accomplish covert identification, a task of great importance in vulnerable security facilities such as
airports and banks. Finally, it is worth mentioning that the low complexity and low cost of the new
eye tracking devices enable the implementation of internet based identification systems, that are
nowadays important for a class of modern technological applications such as e-consuming, e-banking
services and private databases.

The remaining of this paper is organized as follows. In Section 2 we discuss the previous efforts
that established the newborn area of eye movement exploitation on biometric systems. The main spots
of our methodology are further explained here. Section 3 provides an informative description of the
experimental implementation, highlighting the importance of the chosen stimuli consisting of face
photos, which expresses our intention to extract merely behavioral information. Section 4 fully describes the novel graph-based procedure that has been adopted for the processing stage of the signals and Section 5 provides an evaluation of the extracted results and a comparative assessment of our method against previously employed features/techniques. Finally, Section 6 includes some conclusion remarks and future ideas for the extension of this work.

2. Previous work

The research interest involving the exploration of eye movements in the field of biometrics is rather recent, showing already some promising results and a great potential for further development. Kasprowski and Ober (2004) inspect the possibility of using human eye movements as a framework for biometric identification. In their work, the optic stimuli consisting of a moving spot, is presented to the subjects whereas simultaneously an eye tracking system records their eye movements. Cepstrum features are extracted from the captured signals during the processing stage and a set of classification schemes is afterwards applied for the evaluation of the method. The resulting FAR (False Acceptance Rates) and FRR (False Rejection Rates) provide a strong motivation on further exploration of human eye movements for biometric purposes. The employment of a simple moving spot as optic stimulation however, restricts this method on checking mostly physical aspects of the oculomotor (eye controlling) system of each subject than inspecting clearly behavioral characteristics. Bednarik et al. (2005) step further using both moving spots and static images as stimuli in their experiments. They explore a number of possible features such as the pupil diameter, gaze velocity and distance between the eyes. Their most promising results though, arise mostly from physical-dependent characteristics such as the distance between the eyes. Komogortsev et al. (2010) adopt a different philosophy in the exploitation of eye movements by using them as an optimization framework for the OPMM (Oculomotor Plant Mathematical Model, Komogortsev and Khan, 2008), a theoretic mathematical model which describes the movement of the eyes. Their experimentation suffers from the same lack-of-behavioral aspects found in Kasprowski and Ober (2004), as they use a jumping point for visual stimulation too. Finally, Kinnunen et al. (2010) try to
develop an eye movement processing method for signals coming from the observation of free type
stimuli sources. Their strategy follows a task independent optic scenario and they employ a Gaussian
Mixture Model in order to build features that would work in an unrestricted environment.

Our proposed work attempts on expanding the current eye movement research in the field of
biometrics, incorporating not only the physical but mostly the behavioral characteristics of the
underlying brain mechanisms that are reflected through the movement of the eyes. For the first time
we select an innovative visual stimuli consisting of human face images. The special position
possessed by human faces as visual stimulation is highlighted through the discoveries of advanced
research studies in the sciences of neuropsychology and neuroimaging. Since the late 70’s certain
idiosyncrasies were observed during face processing tasks (Walker-Smith et al., 1977), whereas the
findings by (Farah et al., 1995), (Kanwisher et al., 1997) further argued that the mechanisms of human
face perception depend on dedicated neural systems and procedures. Moreover, in (Henderson et al.,
2005) the functionality of eye movements is explored while subjects observe human faces,
concluding that eye movements play an important role in human face perception. These inspiring
findings provided us with the motivation on employing images depicting human faces as a visual
stimulation in our experiment. As human faces are processed in an idiosyncratic way by each person,
eye movements should in this case reflect to a certain extent special behavioral characteristics of the
individual. Our research involves the exploration of the degree that these features can serve for the
identification of subjects, based on our processing strategy for the eye movement signals. In addition,
a novel graph based comparison scheme has been chosen to quantify the similarity of the spatial
distributions formed by fixation points, in an effort to investigate mainly behavioral inter subject
differences. Current biometric research that concerns methods which depend on physical features is
well established and has reached high levels of accuracy, so we propose that behavior-based
biometric research should advance further as it offers unique advantages for implementation
in unconstrained biometric systems.
3. Experimental procedure

3.1. Participants

The experiment was conducted with the participation of 15 volunteers (12 males / 3 females) aging in a range of 20-30 years old. The vast majority of them did not have previous experience with an eye tracking device. No specific task instructions were given to them other than freely observing the face images that would be presented on the stimuli screen.

3.2. Apparatus

The recording of eye movement trajectories was accomplished with the use of a 50 Hz infrared Dual Purkinje CRS Eye Tracker (Cambridge Research Systems) which provides a tracking accuracy of 0.125-0.25 degrees and a horizontal/vertical range of ±40/±20 degrees. The subject’s head was comfortably placed in the correct position by the head rest mounted on the device, allowing ±12 millimeters of head movement. The image stimuli was presented on a 19 inch monitor and the samples were acquired and stored with the use of the Matlab Video Eye tracker Toolbox running on a Windows Pentium 3 GHz, 4GB RAM system.

3.3. The Experiment

Each participant is placed at a viewing distance of 60cm in front of the stimuli screen where a preliminary calibrating stage takes place. Calibration is essential for the subsequent experimental procedure in order to obtain a correct correspondence between the eye movement signals and the position of the image stimuli on the screen. Following this initial step, the main sequence of images is presented, consisting of ten photos depicting real human faces taken both from the stuff of our laboratory and from Tarres F. and Rama A. “GTAV Face Database”. The total time of an experimental session is forty seconds (4 sec. for each image), and in this period eye movements of the subject are recorded and stored for further processing. The experimental procedure is repeated, with the same images presented in a different order. From each repetition ten eye movement trajectories are obtained, and the experiment is repeated eight times for each of the participants, yielding in the formation of a database containing 10 x 8 samples for each of the subjects. The implementation details were carefully adopted in order to optimize the extraction of behavioral information from each
subject during the test. We decided to use the same ten face images for all subjects and for all repetitions-sessions of the experiment. Our goal was to examine the differences among eye trajectories that present an inter-subject dependent character than an image-content dependent one, so employment of the same faces appears as a natural selection providing a common ground in the comparison process. An implication that commonly arises in similar types of visual-cognitive experiments is the appearance of learning effects. To overcome such effects we chose to alternate the sequence of images presentation at each session of the experiment. A rearrangement of trajectories takes place upon completion of the test so that we can compare samples that correspond to the same face image. Moreover, an experiment which intends on extracting persistent behavioral characteristics is more appropriate to be implemented in different recording days (different subject conditions), so we decided to split the experiment in two recording days (four sessions each).

4. Processing of eye movement signals

4.1. Feature Extraction

In the proposed method the positions of eye movements (x-y coordinates on the image plane) will be directly employed as the feature to represent each eye trajectory, as shown in Fig.1. The similarity of spatial distributions for the fixation points originating from the same and from different individuals will be quantified via a graph theoretic measure based on the multivariate generalization of Wald-Wolfowitz runs test (Friedman and Rafsky, 1979). Raw eye movement recordings provided by the eye tracking device must initially undergo a preprocessing step, where noisy or outlier samples that contaminate the real eye movement positions should be eliminated. In general the source of noise may be device dependent, as for example in the case of misrecordings or miscalculations of the actual point positions, which can result in the appearance of recording gaps or deformation of the original trajectory. There is an outlier causing source however, which is related to the behavior of the experimental subjects. During the observation of visual stimuli the subject may blink or temporarily loose attention from the image plane, generating thus outlier points that interfere with the original spots of attention. Given our decision to use directly the positions of eye movements as a feature that
informs us about the actual attention locations of the individuals, a robust preprocessing scheme which should accommodate for both outliers and noise seems obligatory.

A graph-based clustering process which involves the formation of a two-round Minimum Spanning Tree structure will be employed in the preprocessing stage, previously introduced for outlier detection and clustering in Zhong et al. (2009) and Zhong et al. (2010). Application of the method yields a dynamic representation of eye fixations and simultaneously reduces the number of outlier points in the samples. Let us suppose that each eye trajectory can be represented by a dataset $\mathcal{X} = \{ x_1, x_2, \ldots, x_i, \ldots, x_N \}$, with $x_i = (x_{i1}, \ldots, x_{id})^T \in \mathbb{R}^d$ is a feature vector (in our case $d=2$ as the features are the x-y positions of the samples). The initial goal of the algorithm is to group these vectors in a number of $K$ clusters $C_1, C_2, \ldots, C_K$ and consequently to decide which of the clusters correspond to actual gazing regions and which are outliers. Let $G(X) = (V, E)$ denote an undirected and weighted complete graph with each edge $(x_i, x_j)$ having a length $\rho(x_i, x_j)$ (here we use the Euclidean distance). Then, we denote $T_1 = f_{\text{mst}}(V, E)$ the MST which can be constructed considering the structure of $G(X) = (V, E)$, where $f_{\text{mst}} : (V, E) \rightarrow T$ is a function to produce MST from a graph. The second round MST of $G(X)$ can be defined as $T_2 = f_{\text{mst}}(V, E - T_1)$. Combining $T_1$ and $T_2$, a two-round MST based graph, say $G_{\text{mst}}(X) = (V, T_1 + T_2) = (V, E_{\text{mst}})$, is obtained. The constructed two-round MST should afterwards be partitioned with a sequence of graph cuts. Whereas in traditional MST-based clustering methods each graph cut leads to a partition, two-round MST needs at least two edges to be removed for a partition to happen, making hence MST-based clustering more robust, as for a graph cut to happen, more evidence needs to be considered. After construction of the two-round MST the edges are ranked according to their two-round MST weights and removed one after another resulting in a set of point clusters. Among these clusters some are valid and represent true fixations but there also exist outlier clusters (for example isolated points or concentrations with a small number of points). The outlier factor $\text{OFC}(C_i)$ (Zhong et al., 2009) of each cluster $C_i$ will be subsequently employed, to come up with a decision of which clusters to recognize as outliers and be removed and the clusters that correspond to real attention spots. The outlier factor represents a value
which is in direct ratio to cluster density, and inverse ratio to cluster cardinality. The resulting clusters
are outlier free as illustrated in Fig.2 and representative prototypes in the form of cluster centroids can
finally be extracted, forming a characteristic x-y signature for each of the face photos in every
repetition of the experiment.

4.2. Graph-based matching of visual fixation signatures

Graph theory provides a dynamic framework for the description of structural relationships among
data, so graph techniques seem as an appropriate selection for quantifying the dissimilarity of the
constructed fixation signatures. In the field of graph object comparison Graph Edit Distance (GED)(a
comprehensive research is offered in Gao et al., 2009), possesses a significant role in a variety of
applications such as graph classification, computer vision and pattern recognition. In this case, a
representative graph is generated representing structural relationships of the data, and vertex labels
may be assigned based on characteristics of the dataset to which each vertex corresponds. Next, this
representative graph is compared to a database of prototype or model graphs to identify and classify
the structure of interest. In this context, graph edit distance provides a good measure for comparing
graphs. The main drawback of graph edit distance is its exponential computational complexity in
terms of the number of graph vertices which is NP-hard in general. Other graph based procedures have
been already used in identification processes, as for example in the field of speaker recognition
(Hautamaki et al., 2008), where graph structures are used to model the centroids resulting from a
preprocessing clustering procedure in the feature space. In their work, during the comparison
phase, the weights of the edges are not taken into account and the similarity between a reference and a
test graph is evaluated by calculating the degree of isomorphism of them. In our paper a different
approach is adopted, which ties better with our particular experimental scenario. Since the used
feature now is the fixation locations, not only the structure but also the weights (distances) among the
points should be considered. In this context we propose a dynamic comparison scheme initiating with
the construction of a joint Minimal Spanning Tree graph structure between a reference and a test
sample and subsequently exploiting the statistics that derive from the distributional attributes of the
point concentrations. This is done by employing the multivariate generalization of the Wald-
Wolfowitz random runs test which has already proved its efficiency at discriminating tasks (Laskaris et al., 2009).

The problem under consideration is that given two 2-D samples corresponding to the generated visual fixations, the hypothesis \( H_0 \) to be tested is whether they are coming from the same multivariate distribution. The first step of the procedure is to build the overall MST of the two samples without taking into consideration the samples identity. Continuing, a test statistic \( R \) will be computed based on the known sample identities. \( R \) is the total number of runs, defining run as being a consecutive sequence of identical sample identities. The rejection of the null hypothesis \( H_0 \) is for small values of \( R \). In practical terms, the test denotes the degree of overlapping between the two distributions.

Consider two data samples of size \( m \) and \( n \), respectively from distributions \( F_x \) and \( F_y \), both defined in \( \mathbb{R}^P \) (in our case the space is \( \mathbb{R}^2 \)). Let \( N = m + n \), \( C \) be the number of edge pairs of MST sharing a common node, and \( d_i \) be the degree of the \( i^{th} \) node.

Then, \( C = \frac{1}{2} \sum_{i=1}^{N} d_i \cdot (d_i - 1) \)

Number the \( N-1 \) edges of the MST arbitrarily and define \( Z_i, 1 \leq i \leq N-1 \), as:

\[
Z_i = \begin{cases} 
1 & \text{if the } i^{th} \text{ edge links nodes from different samples} \\
0 & \text{otherwise}
\end{cases}
\]

Then, \( R = \sum_{i=1}^{N-1} Z_i \cdot 1 \). Under \( H_0 \), the mean and variance of \( R \) can be calculated as follows:

\[
E[R] = \frac{2mn}{N} + 1, \quad \text{Var}[R | C] = \frac{2mn}{N(N-1)} \cdot \left[ \frac{2mn - N}{N} + \frac{C - N + 2}{(N-2)(N-3)} \left[ N(N-1) - 4mn + 2 \right] \right]
\]

It has been shown (Friedman and Rafsky, 1979) that the quantity:

\[
W = \frac{R - E[R]}{\sqrt{\text{Var}[R]}}
\]

(approximately) the standard normal distribution, while \( E[R] \) and \( \text{Var}[R] \) are given in closed form
based on the size of the two samples. This enables the computation of the significance level (and p-value) for the acceptance of the hypothesis $H_0$.

Given two eye fixation samples, we will use the value of $W$ as a measure of their similarity. Specifically, the greater the value of $W$, the most similar the samples are. A visualization of the graph-based comparison procedure is provided in Fig.3 and Fig.4 for the cases of samples deriving from the same and from different subjects accordingly. Starting with the point distributions, their joint MST is built and the $W$ value is calculated based on the MST statistics. It can be confirmed that the value of $W$ is greater in the case that the samples are coming from the same person than of these coming from different subjects. An implication which may arise in situations of free viewing experiments is that the observed differences may be attributed to content dependent than clear inter subject dependent sources. To surpass this problem the fixation signatures should be compared independently for each different face image as our purpose is to evaluate the inter subject differences in the way that a face image is processed. So, in order to compare the signals that are produced during each session we pairwise compute the $W$ values for every image corresponding to the same face and we take the mean as the value of similarity for the eye signals generated in each experimental session. In this way a similarity matrix containing the $W$ values for all experimental sessions among all subjects is built and is consequently fed to the identification system.

5. Performance evaluation

The efficiency of the proposed scheme was evaluated by means of a frequently used identification performance measure, the EER (Equal Error Rate), which corresponds to the point of a system’s operation where FRR (False Rejection Rate) equals the FAR (False Acceptance Rate). The similarity matrix which has been assembled in the previous step feeds a moving threshold Nearest Neighbor classifier through which the ROC curve demonstrated on Fig. 5 is obtained, revealing an EER of nearly 30% for the current implementation. This value lies on the same levels or in many cases outperforms the previous reported results in (Kasprowski and Ober, 2004), (Bednarik et al., 2005), (Kinnunen et al., 2010), (Komogortsev et al., 2010). Considering the fact that our experimental
method intends on engaging mostly the behavioral features of eye movements than the physical characteristics of the oculomotor system, the importance of this performance rate is further emphasized, showing the potential on the extraction of behavioral patterns from human eye movements.

Next and in a diverse experimentation scenario, the present implementation was also compared against a set of features/methods that were selected from the previous research efforts, in order to explore the capabilities of each method to separate individuals according to their eye trajectories. The eye movement data upon the features/methods have been tested are the trajectories that were collected throughout our experiment. In this way the performance of each method in a behavioral free viewing scenario was supplementary inspected. The results of this comparative test are demonstrated at Table 1. In the first method, Cepstrum features were extracted from each eye movement waveform following the scenario in Kasprowski and Ober, 2004. The resulting identification rate seems lower than the one achieved in their jumping point experiment. This may be attributed to the spectral nature of their chosen feature that matches in constraint viewing situations, where mainly oculomotor inter subject differences are observed, but may appear inadequate in a free viewing scenario, where behavioral characteristics become active too. Next, the efficacy of gaze velocity and pupil diameter dynamics, adopted by Bednarik et al., 2005, was also explored. Feature extraction was accomplished through FFT followed by a PCA processing stage, since this cascade operation constantly outperformed the identification rates that were achieved by using FFT and PCA alone. The results seem in consistency with these obtained by Bednarik et al., 2005, with gaze velocity feature presenting poor rates whereas pupil diameter achieves medium rates of around 55%. Finally, the method of Kinnunen et al., 2010, though demonstrating promising results, was considered inappropriate to be tested with our experimental data since their method demands lengthy observation times for the training phase of the UBM (the background model) - up to 7 min to get respectful results. In our scenario, the stimuli is of free viewing type too, however it cannot be susceptible to long observation times, since face exploration usually lasts a couple of seconds. The results in the last row of Table 1, demonstrate obviously that the graph based processing technique that has been adopted in the current work offers superior identification rates compared with the other tested methods. Such a scheme
allows for a robust comparison of the fixation point distributions directly on the image regions, making thus easier the verification of idiosyncratic characteristics in a free viewingscenario when compared withtechniques that rely mostly on time/frequency characteristics.

6. Conclusions

A novel experimental and processing scheme was proposed in this paper, aiming at the extraction of behavioral aspects that are reflected in human eye movements and the possible exploitation of them in the biometrical field. The results seem promising indicating the presence of idiosyncratic patterns that can be deployed for discriminating individuals. The obtained EER portrays the difficulties yet existing in the implementation of a real-time standalone application totally depending on behavioral features extracted from human eye movements. However, a feasible possibility is the application of the present approach in conjunction with high-identification accuracy methods based on physical features in order to build a hybrid physical-behavioral identification system that embeds the special advantages arising from the dynamic nature of behavioral features. This work attempts to progress the newly established domain of eye movements exploration on biometrics, highlighting the advantages offered by the use of behavioral features and the need for bridging the gap between high accuracy physical features and the brain activity based characteristics. Future guidelines involve the exploitation of latest technology eye tracking devices (high frequency, head-mounted free move devices) which should allow more dynamic neuropsychology experiments and may facilitate the extraction of additional behavioral features.

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Table 1 Performance of selected features against the proposed method (data from our experiment)

<table>
<thead>
<tr>
<th>Feature/Classifier</th>
<th>KNN (k=1)</th>
<th>KNN (k=3)</th>
<th>SVM (RBF kernel)</th>
</tr>
</thead>
<tbody>
<tr>
<td>pupil diameter (fft-pca)</td>
<td>54.2%</td>
<td>56.1%</td>
<td>55.4%</td>
</tr>
<tr>
<td>gaze velocity (fft-pca)</td>
<td>15.3%</td>
<td>19%</td>
<td>17.2%</td>
</tr>
<tr>
<td>Cepstrum features</td>
<td>41.3%</td>
<td>44.5%</td>
<td>43.1%</td>
</tr>
<tr>
<td>x-y positions/ graph based matching</td>
<td>67.5%</td>
<td>70.2%</td>
<td>68.8%</td>
</tr>
</tbody>
</table>
Fig. 1 Fixation points on the face stimuli and the corresponding feature on the x-y plane.
**Fig. 2** Two-round MST construction on raw fixation data and the resulting outlier 'clean' clusters.
Fig. 3 Construction of the overall MST for eye data samples originating from the same subject.

subject 1 - sample 1

subject 1 - sample 4

joint MST

$R = 19$

$W = 0.64$
Fig. 4 Construction of the overall MST for eye data samples originating from different subjects.

subject 1 - sample 1

subject 3 - sample 1

joint MST
\[ R = 12 \]
\[ W = -2.89 \]
Fig. 5 ROC curve for the present implementation. An EER of nearly 30% is obtained.
• The possibility of eye movements deployment on biometrics field is examined.
• We preprocess raw data with a graph theoretic outlier robust clustering scheme.
• We employ a graph based measure for comparison of visual fixation signatures.
• Resulting EER shows potential in the use of eye movements for human identification.