Pattern Recognition Letters
journal homepage: www.elsevier.com

Eye movement analysis for human authentication: a critical survey

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ABSTRACT

This paper addresses the active and dynamic nature of biometrics, in general, and gaze analysis, in particular, including motivation and background. The paper includes a critical survey of existing gaze analysis methods, challenges due to uncontrolled settings and lack of standards, and outlines promising future R&D directions. Criteria for performance evaluation are proposed, and state-of-the art gaze analysis methods are compared on the same database set. Performance improvement would come from richer stimuli including task dependent user profiles, with applications going much beyond identity management to include personalized medical care and rehabilitation, privacy, marketing, and education.

Keywords: Gaze analysis; Active and dynamic biometrics; Eye movements; HCI; Identity management; GANT; Gaze scan paths; Performance evaluation; Uncontrolled settings

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1. Introduction

Face, fingerprints, and iris are the most widely used biometrics for personal identification. They provide characteristics in terms of personal appearance, are usually passive in nature, and are employed for forensics, identity management, and security purposes [1]. Personal characteristics, however, are all-encompassing. They can also be active and dynamic in nature and involve therefore change, drift, and transient behavioral traits associated to cognitive and/or emotional states. Behavioral characteristics, that consider the temporal aspects of identity in action, include gait, signature dynamics, e.g. speed and acceleration, keystroke dynamics [3], and eye movements. The latter, the subject of interest for this paper, refers to unconscious eye movements (saccades) and gaze scan paths. This paper examines in particular the dynamic aspects of eye behaviors with the purpose to assess the relevance of interpreting data-driven eye movement patterns as behavioral biometrics for the purpose of identification.

A biometric recognition system based on eye movements usually consists of three components:

- Stimulus: one or more stimuli can be used to trigger eye movements. The stimuli include among others text, moving objects, video, and face pictures.
- Eye-tracker: the eye-trackers record the eye movements. They can be divided in two major groups, head-mounted eye-trackers and remote eye-trackers [43]. The head-mounted ones record the gaze from a short distance and are usually more accurate. On the other hand, the remote eye-trackers record the gaze from a distance and do not require the user to wear specific devices.
- Gaze descriptor: raw eye movement data, without further analysis, are for the most part meaningless [8] and therefore need to be properly modeled for ultimate authentication and/or interpretation.

This paper provides first a survey on eye movements analysis for human authentication including a critical analysis of the pros and cons, depending on the application scenario of the techniques reviewed. The paper then provides a comparative performances assessment of three major but similar gaze analysis techniques based on a graph representation of the human gaze. The techniques were originally tested on different databases and thus difficult to assess but here they are compared on a larger and unique dataset to reach meaningful and valid conclusions.

The outline of the paper is as follows. Section 2 introduces eye movements and stimuli, while section 3 reviews eye tracking techniques and current popular devices. Section 4 surveys representative research that exploits eye characteristics and their dynamics for biometric identification purposes. Section 5 describes three state-of-the art gaze analysis methods, Rigas et al., GAS, and GANT, and comparatively evaluates them in section 7. Section 6 present a list of qualitative and quantitative criteria used to evaluate the eye movement analysis techniques. Section 8 discusses the current and future potential for gaze analysis. The paper concludes in Section 9 with a summary of our findings.

2. Eye movements

Experiments have shown that while it is possible to move one's attention without shifting the gaze, the opposite is more difficult. According to Hoffman [11], visual attention is always a little (100-250 ms) ahead of the eye, and when attention moves to a new position, the gaze moves there too [12]. Apart from the different attention theories developed to date, what is certain is that (covert) attention is strictly correlated to eye behavior and the orienting mechanisms used to make inferences about spatial layout and object identity. Attention mechanisms, which vary from person to person

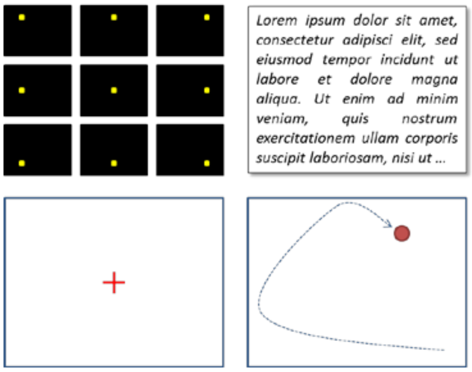

Figure 1. Eye movement stimuli: top-left, jumping-point; top-right, text; bottom-left, static cross; bottom-right, moving object.

(due to personal background, physiological make-up, and training), can therefore be gainfully used for biometric identification [49][50].

Eye movements occur as very fast, almost instantaneous, saccades (whose duration is usually less than 100 ms), alternating with fixation periods of about 100-600 ms (characterized by a relative stability of the eye). During saccades, we are relatively speaking blind. We see only during fixations, while the eye is holding still [60]. These eye movements usually take place in response to specific stimuli or mental processes. Research has been carried out to discover relations between eye behaviors and emotional states (e.g., in the context of e-learning [13], [14]) or to analyze the cognitive processes in a variety of tasks (e.g. in reading film subtitles [15]).

In order to trigger eye movements, a wide number of different stimuli have been investigated. One of the most employed stimuli is the so-called "jumping point." It can be a LED or a point displayed on a screen. The point appears (or the LED lights up) in predefined positions, e.g. at the intersection points of a 9x9 grid, and the human observer is asked to follow with her gaze the jumping point. Since the fixation positions are fixed, i.e. where the jumping point appears, the main information exploited here is related to saccades.

The second traditional stimulus is the text. The observer is involved in a text reading task; the text can be displayed on a screen for better eye tracker calibration. The reading task provides that the observer scans the text line after line. Thus, the scanning path is somehow defined. However, the horizontal scan path can vary (e.g. in terms of speed) from person to person. The unconscious eye movements (saccades) are mainly exploited for the eye movement analysis.

Even simpler than the jumping point, the static cross stimulus has been successful and achieved 90% correct classification [20]. It displays a small cross at the center of the screen and records the saccades originated from the observer's eyes.

Another way used to trigger eye movements would require following a moving object. This stimulus is usually realized by displaying the moving object (e.g. a cross, a circle, or in general a geometrical shape) on a screen. The above mentioned stimuli share the fact that the gaze path is defined by the stimulus itself. The eye movements recognition systems based on those kinds of stimuli leverage on saccadic movement analysis to perform biometric recognition. An illustration of the above mentioned stimuli is given in Figure 1.

Grey-scaled or colored images have been successfully used as stimuli in eye movement analysis. Two possible modalities can be adopted: free viewing and task based observation. In the free viewing of scenes, the observer can freely look at the displayed image for a determined time. In the task based modality the observer accomplishes a predetermined task, e.g. finding an object in the image, see the photographs and decide if she knows the face by pressing yes/no button [39]. A face image stimulus example is presented in Figure 2.

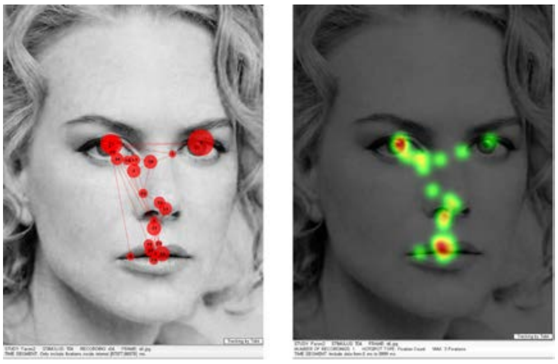

Figure 2. Gaze Path: illustration of face image stimulus.

Video provides complex information about the observer's gaze behavior because they display dynamic scenes and can trigger emotional reactions. Images and videos are mainly employed as stimuli when not only the saccadic movements have to be analyzed but also the fixations points, i.e. the gaze path. In fact, some works, e.g. [31], only rely on the fixation point coordinates.

3. Data capture and tracking

According to Nielsen and Pernice [42] "Eye tracking is simply following the trail of where a person is looking." The information connected to eye movements is measured through an eye tracker, tracking the time, duration and location of eyes' fixations and the saccades between fixations.

Four categories of methods for eye tracking can be identified. They include electro-oculography (EOG), scleral contact lens / search coil, photo-oculography (POG) or video-oculography (VOG), and combined pupil-corneal reflection [8].

The EOG method is based on the measurement of differences of the electrical potential detected by four electrodes placed on the skin just above, below, on the left and on the right of the eye. The electrodes detect the changes in voltage due to eyeball movements. Although this solution is very cheap, it is not very accurate. In addition, EOG is often noisier than other approaches, e.g. VOG, because the electric signals originating from facial muscle movements due to talking, smiling, frowning or eye-blinking, interfere with the eye movement signal recording [51].

The method based on scleral contact lenses and "search coil", on the other hand, is one of the most accurate, but also very invasive. The gaze direction is estimated via a mechanical (or optical) reference object mounted on a contact lens that covers both the cornea and the sclera. A stalk attached to the lens is then connected to a mechanical or optical device, such as a coil that measures the variation of an electromagnetic field.

VOG is based on image processing, a video sequence (or several photos) is analyzed to extract a set of eye characteristics during rotation and translation movements including the pupil's shape, the edge separating sclera and iris and corneal reflections caused by one or more (usually infrared) light sources.

The above mentioned approaches measure the position of the eyes relative to the head, while the combined use of corneal and pupillary reflections disambiguates head movement and eye rotations. This technique is based on the analysis of the light reflections (usually from infrared light sources) on the cornea and their relative position with respect to the pupil center. The eye trackers based on this technology, usually integrate near infrared light sources that direct a beam of light on the observer's eyes. The reflection patterns produced on the cornea and the pupil are captured by a sensor mounted on the device. The pupil is easily detected thank to the bright pupil phenomenon occurring when the eye is exposed to near infrared light [7][53]. Advanced image-processing algorithms and a physiological 3D model of the eye are then used to estimate the position of the eye in space and the point of gaze with high accuracy[1]. The gaze direction estimation obtained is very accurate [44].

Eye trackers can be divided in two major categories: head-mounted and remote eye trackers. In the following we will briefly review the most popular devices.

3.1. Head-mounted eye trackers

The advantage of the wearable solution is that little calibration is required, while the disadvantage is that the user is required to wear the device, making this approach intrusive and suitable only in a limited number of scenarios.

In the works reviewed in this paper, the following wearable eye trackers have been employed. The Ober 2 (Permobil Meditech AB, Sweden) [46] eye tracker employs goggles and is based on the corneal and pupillary reflection analysis. The Visual Eyes (Micromedical Technologies, UK)[2] eye tracker, is based on the VOG technology. The version of this device used in [20], consists in a wearable video camera system with a resolution of 320×240 and sampling frequency of 30 Hz. Finally, the Eye Link II (by SR Research)[3], is a 500 Hz binocular eye monitoring, consisting of three miniature cameras mounted on a padded headband.

3.2. Remote eye trackers

Remote eye trackers are less intrusive, although nowadays solutions usually require stabilizing the head by chin and/or forehead resting. In this category of eye tracker, we can further distinguish the monitor embedded solution from the standalone eye tracker.

The advantage of the monitor embedded eye trackers is the simple system set-up, since the screen is already in the correct position with respect to the eye tracker. The most employed devices belonging to this category are from Tobii AB[4], e.g. Tobii ET-1750, Tobii TX300, and Tobii 1750. As an example, the Tobii 1750 integrates all components into a 17'' LCD monitor (1280×1024 resolution) and the frame rates are about 50 Hz.

Standalone eye trackers include the Tobii X120 and the EyeLink 1000[5]. The latter provides two different set-ups: head supported (2000 Hz Monocular / 1000 Hz Binocular) and remote / head free (500 Hz Monocular).

In [31], a 50 Hz infrared Dual Purkinje CRS Eye Tracker (Cambridge Research Systems) [6] has been employed. The eye tracker illuminates the eye with an infrared beam and employs a complex combination of lenses and servo-controlled mirrors to continuously locate the positions of the first and fourth Purkinje images. These Purkinje images are formed by light reflected from surfaces in the eye[7].

Beyond the eye trackers, other devices, originally developed for other purpose, have been used for tracking eye movements.

A simple webcam has been employed in [22], while a device designed for PlayStation 3, namely the PlayStation Eye, with a temporal resolution of 75 Hz and average calibration accuracy of 1.1°. This has been possible thanks to specific software to process the output of "simple" video cameras for eye tracking, such as the open-source ITU Gaze Tracker software [54].

Poole and Ball [7] provide a succinct but helpful introduction to eye tracking in human-computer interaction and usability research. More recently, Duchowski [8] has authored an important and throughout monograph on eye tracking methodology. Hornof and

[1] http://www.tobiipro.com/learn-and-support/learn/eye-tracking-essentials/how-do-tobii-eye-trackers-work/
[2] http://www.micromedical.com/Products/VisualEyes-VNG
[3] http://www.sr-research.com/EL_II.html
[4] http://www.tobii.com/
[5] http://www.sr-research.com/EL_1000.html
[6] http://www.crsltd.com/tools-for-vision-science/eye-tracking/high-speed-video-eye-tracker-toolbox/
[7] https://ppw.kuleuven.be/home/english/research/lep/resources/purkinje

Halverson [10] discuss calibration for better accuracy and how to remove systematic errors in eye-tracking data.

4. Eye movement analysis

Gaze analysis is often employed in Human-Computer Interaction (HCI) to analyze the usability of computer interfaces. In [55], eye tracker technology is used to assess the usability of the University of Žilina website. A similar approach is adopted in [56] to study the banner positioning of online newspapers. In [48] demographic data and behavioral data, namely gender recognition and gaze analysis, are combined to investigate the possibility of providing more adaptive and interactive advertising. Cantoni and Setti [57], present a preliminary qualitative analysis, of the image boundary detection performed by human gaze, by recording eye movements during the observation of an illustration of two combined entities. Activity Recognition, in particular of the following tasks: read, browse, write, watching a video, and copy; is obtained by the use of an EOG based system in [45], with an average precision of 76.1% and recall of 70.5%. Visual processes occur both overtly and covertly, and it is just the covert modality that is strictly connected to a person's cognitive and psychological processes [21]. In [58], eye movement analysis is used for diagnostic assessment of disorders of consciousness. In [52], a novel eye-gaze driven technique for surgical assessment and workflow recovery is presented. As an example of more recreational application of eye tracking, in [47][59], the latter is used to facilitate aiming in computer gaming. In [2], an eye tracker is employed to capture the iris for real-time continuous recognition.

4.1. Eye movement analysis in biometrics

The dynamics of gaze ("behavioral") biometrics are multi-faceted. They probe both cognitive and emotive states. In particular, the so-called Eye-Mind Hypothesis [16] states that there is a direct correspondence between the user's gaze and his or her point of attention. Fookes et al. [9] co-authored a unique monograph on the all-encompassing behavioral biometrics for human identification and intelligent applications, with one chapter dedicated to gaze based personal identification and two other chapters delving in security and evaluation of behavioral biometric systems.

Kasprowski and Ober [17], survey previous research on eye movements (the gaze point coordinates) of subjects while following a jumping point on the screen and confirmed that behavioral biometrics characteristic of data-driven eye movements (e.g., saccades), are difficult to spoof, and can be leveraged for subject identification.

Bednarik et al. [18] exploited various kinds of eye data, including pupil size and their dynamics, gaze scan speeds, and distances of infrared reflections on the eyes. They also investigated the use of a number of different stimuli, including text and moving object, with the static cross stimulus performing the best and achieving an identification rate of 90%.

Cuong et al., in [19] comparatively evaluated the Mel-Frequency Cepstral Coefficients (MFCCs) for encoding various eye-tracking features for eye-tracking classification. They further showed that MFCC compare favorably to using any of the Fourier transform, cepstrum, or raw representations.

Zhang and Juhola [20] differentiated between different eye movement types such as saccade, nystagmus, smooth pursuit and vestibulo-ocular reflex eye movements, and noted that saccades are predominant. More recently, Juhola et al. [35] compared eye movements measured by EOG and movement signals given by VOG system, with EOG performing the best (Identification Rate of 97%).

Deravi and Guness [22] recorded gaze trajectory data of human subjects while looking at some images for about 5 s each. Gaze durations, pupil positions, pupil sizes and gaze points were measured and then fed to feature selection algorithms.

Holland and Komogortsev [23] assessed the effects of eye tracking specification and stimulus presentation on the biometric feasibility of complex eye movement patterns. Through two experiments, they examined the effects of varied temporal resolution, stimulus type, and spatial accuracy. The authors found that, for biometric purposes, eye trackers with spatial accuracy of less than 0.5° and a sampling frequency greater than 250 Hz are most suitable.

The combination of eye behaviors and iris structure provides better recognition rates. As an example of multi-modal data fusion, Komogortsev et al. [6] have proposed a biometric approach that combines and exploits three different eye features, specifically the eye anatomical properties (using OPC), visual attention strategies (using Complex Eye Movement patterns), and the physical structure of the iris. Results indicate that combining three ocular traits improves accuracy, yielding a HTER (Half Total Error Rate) of 19%.

Instead of static images, other investigators consider video clips as stimuli. Kinnunen et al. [24] proposed a task-independent rather than a task-dependent scenario as it is usually the case, in which short-term eye gaze direction is used to build feature vectors modeled by means of Gaussian mixtures. Eye movements, recorded while watching a 25 min long video, are described as a histogram of all the angles the eye spans during a certain time period. The results reported suggest that in eye movements there are person specific features that can be modeled in a task-independent way. This is important, as it suggests that the range of possible applications [25] extends beyond the security-type of authentication to proactive and user-convenience systems.

Liang et al. [26] presented a video-based biometric identification method in which visual attention features are extracted from eye movement recordings and employed as biometric traits to recognize people and show that video-based gaze analysis is a viable solution for biometric applications.

Rigas et al. [36] investigated recently the efficiency of a multi-stimulus and multi-biometric fusion scheme. Diverse visual stimuli (jumping-point-of-light, text, and video), were analyzed with different and appropriated techniques and efficiently combined via a weighted fusion scheme. The best result achieved is a Rank-1 Identification Rate of 88.6% and an Equal Error Rate (EER) of 5.8%. The technique has been tested on a large database of 320 subjects.

Additional biometric traits related to eye tracking include eye movements' acceleration and saccadic velocity, which are extracted from recordings of a person's gaze while looking at visual stimuli [27]. Eye tracking approaches are interesting because they allow the realization of continuous intrusion detection methods, characteristic of active authentication and re-authentication. The ultimate goal here is to identify imposters as those users showing "abnormal" behavior, which is different from behavior shown by legitimate users.

Substantial discrepancies in eye activities may alert the system and possibly lock-up its further use to prevent nefarious activities. For example, Holland and Komogortsev [28] have presented a variety of eye movement-based biometric features, e.g., fixation count, average fixation duration, average saccade amplitudes, average saccade velocities, average saccade peak velocities, the velocity waveform, scan path length, scan path area, scan path inflections, regions of interest, the amplitude-duration relationship, the main sequence relationship, and the pair wise distance between fixations, and their capability to correctly differentiate between subjects. The same authors further comment that the "eye movements are uniquely counterfeit resistant due to the complex neurological interactions and the extraocular muscle properties involved in their generation".

Biedert et al. [29] based their intrusion detector for active authentication on learning effects, while assuming that legitimate users become progressively more accustomed with the execution of certain tasks. In some experiments, the students tested were asked to perform common tasks such as check for emails, read messages from

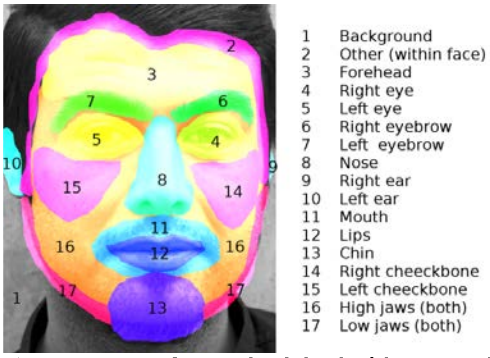

Figure 3. AOI mask: a graphical sketch of the AOI mask.

their imaginary supervisor and perform specific actions connected with their hypothetical thesis work. The authors conclude that "gaze behavior is most discriminative with static and repetitive stimuli."

An interesting question worth additional study would test if gaze analysis supports gender identification as one of the steps needed for dynamic stratification leading to partitioned galleries suitable for ultimate identification. Some steps in this direction have been made in [41] by Galdi et al., where gaze features extracted by the GANT technique [5], are used for demographic categorization, and in particular for gender and age identification.

5. Overview of Rigas et al., GAS, and GANT for comparative evaluation

In this section we present three works that share a common feature: stimuli available to observers consist of face images. The aim of the three methods is to determine the observer identity by the way he/she "gazes" at face images. The use of stimuli such as images of the face requires a low degree of user cooperation and should be thus preferred. Even if faces share the same basic set of features, using the same canonical geometry and all the people display approximately the same areas of the face [30], the three methods considered here demonstrate that each person has a slightly different way to observe a face. In the following we describes in detail each of the three methods and defer to section 6.1 to present their experimental evaluation on the same database (see section 7.1) in order to compare their performance.

5.1. Rigas et al.

The work by Rigas et al. [31] focuses on the free observation of face images. In each one of the eight test sessions carried out, participants, lacking prior experience with an eye tracking device, watch ten photos depicting human faces for 4 s each. Gaze positions were used in a straightforward fashion to build eye trajectories. The similarity of spatial distributions of fixation points was quantified by means of a graph theoretic measure based on the multivariate generalization of Wald–Wolfowitz runs test. The results obtained indicate the existence of characteristic patterns that can be potentially exploited to discriminate among different subjects. 15 volunteers participate in the study, 12 males and 3 females. As the fixation point positions are directly used to build a graph representing the observer's eye trajectory, this method is not scalable. In fact, as the number of fixation points increases the computational time required to build the observation graph greatly increases because, as reported in [31], the algorithm employed requires computing at least three minimum spanning trees, two for the outlier detection phase and one for the matching phase. Finally, the size of the database on which the algorithm has been tested in [31] is too small to assess the algorithm's performance reliably.

5.2. GAS

In [32], as the input images used as stimuli are all faces, it has been possible to define a limited set of areas of interest (AOIs) that are always the same for all the observed images, even if their locations and dimensions can slightly change depending on the specific image. For this reason, GazePoint coordinates have been normalized and quantized according to the AOIs. The dimension of the feature vector therefore is fixed in advance and equals the number of AOIs. In particular, each AOI is assigned an entry into the feature vector, which records the relative (total) time spent looking at that AOI. The feature vectors do not take into account the number of visits for each AOI. If an observer spends some time on an AOI, quits and goes back to it later, only the total amount of time spent by the observer on that AOI is considered and aggregated by summing up the durations of both observations. Figure 3 shows an example of a face together with its AOIs marked with different colors and labeled with integer values. For the purpose of identification different metrics quantify the distance between vectors and rank candidates in terms of similarity. Empirical studies performed by the authors have used several metrics (Euclidean, Jaccard, Spearman, City Block, Cosine, and Correlation), with results reported only for the Euclidean and Cosine distances, which were found to yield the best recognition accuracy.

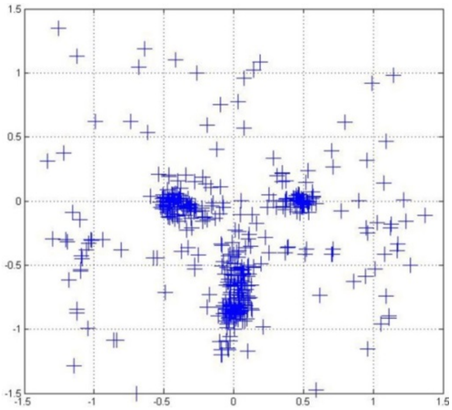

Figure 4. Cloud of normalized fixation points of observer #25 in session 1: merging of observation points coming from all the 16 observed face images.

5.3. GANT

Expanding from the work by Galdi et al. [32], in [5] the information about the time spent by the user gaze in a specific area of the face is acquired with a different and face-position-independent approach. The fixation point coordinates are normalized using the distance between eyes and the distance between eyes' middle point and mouth. This kind of normalization assures that all the points from different images relative to the same face area (e.g., left eye) will fall around the same point (corresponding to the normalized position of the left eye) in the normalized cloud of points (see Figure 4). With respect to previous work, it is thus not necessary to design a mask for each face image. The cloud of fixation points is then subdivided with a grid used to build a graph representing the number of fixation point in each cell, the sum of the duration of the fixation points in each cell, and how many times the user's gaze moved from a cell to another. It is interesting to note that this graph-based approach can be applied on any kind of image. The graph obtained is represented by matrices, with one matrix for each feature (density, duration and arcs). To compare different observers based on densities, durations or arcs, the distance between couples of matrices of the same feature is measured through the Frobenius norm of the matrices' difference.

6. Gaze analysis techniques evaluation criteria

In this section we propose a list of criteria used to assess the gaze analysis methods presented in sections 4 and 5. The criteria used to make individual assessments are not exhaustive and can include:

- ***Experimental setup:***
  - **Distance from device**: a higher distance from the device is desirable since it would allow to develop system requiring less user cooperation;
  - **Device** used for gaze acquisition, e.g. head-mounted or at distance capture device. Remote eye trackers are preferable since they

can collect eye movements in an unobtrusive way;

- **Stimulus**: which kind of stimulus has been used?
- A limited **acquisition time** is desirable to speed up the recognition process.

- ***Database and evaluation criteria:***
  - **Database size** is an important key factor to assure the reliability of the results obtained. A database of a minimum of 50 different subjects is desirable;
  - **Number of acquisition sessions**: behavioral biometrics is affected more by change over time than the physiological biometrics. Temporal performance, including large time intervals, becomes an important factor, if not the decisive one, for GA;
  - **Performance Measures**: number of parameters used to fully defined the methods used, which affects generalization, FAR, FRR, EER, HTER, weighted combination of techniques (data fusion of), if used;
  - **Evaluation protocol** assessment: is the evaluation protocol adopted strong?
  - **Evaluation over time**: comparative evaluation over samples of the same subjects acquired over time.
- ***Method description:***
  - **Acquired data**: what kind of data has been acquired?
  - **Feature extracted**;
  - **Feature Vectors Size**: feature selection and dimensionality reduction. Relation between the dimension of the feature vector and performances in terms of accuracy;
  - **Classifier**;
  - **Number of soft biometrics** used in the proposed framework: Gaze Analysis (GA) is used alone or in combination (data fusion) with one or more soft biometrics;
  - **Number of hard biometrics** used in the proposed framework: Gaze Analysis (GA) is used alone or in combination (data fusion) with one or more hard biometrics (iris and\or face);
  - **Static/Dynamic modality**: Gaze Analysis considers only a static aspect, such as the topology of the scan path, providing a one-shot representation of the biometric trait, or even dynamic aspects, especially related to the speed and direction of fixations;
- ***Final results, Reproducibility and Novelty:***
  - **Experimental Protocols and Replication**: is enough information available to duplicate experiments, and are data sets used standard and/or available for others;
  - **Theory and Practice**: merit and novelty for the discrimination method proposed;
  - **Results**: final results obtained.

We evaluate representative methods for human recognition based on gaze analysis along with the three methods presented in section 5. From the list of criteria, we identify a set describing the experimental setup (see Table 1), a set concerning the database characteristics and the evaluation criteria adopted (see Table 2), in

Table 3 we identified a set of criteria to describe the methods, and, finally, in Table 4, we present the final results obtained by each method along with an evaluation of its reproducibility and novelty.

Table 1 Experimental setup. Abbreviations: EOG - Electro-oculographic; VOG - Video-oculogram.

Method	Distance from device	Device	Stimulus	Acquisition time
Kasprowski and Ober, 2004 [17]	Head-mounted eye tracker	Ober 2	jumping point	10 s
Bednarik et al., 2005 [18]	80 cm	Tobii ET-1750	text reading, static cross, static gray-scaled image, moving red cross	< 5 min in total 4 s for the static cross task
Kinnunen et al., 2010 [24]	1 m	Tobii X120	video	25 min
Deravi and Guness, 2011 [22]	30-60 cm	Webcam	images	40 s
Holland and Komogortsev, 2011 [28]	Head-mounted eye tracker	Eye Link II	text	1 min
Cuong et al., 2012 [19]	Head-mounted eye tracker	Ober 2	jumping point	8 s
Zhang and Juhola, 2012 [20]	Head-mounted eye tracker	Visual Eyes	jumping point	64 s
Komogortsev et al., 2012 [6]	70 cm	EyeLink 1000	jumping point	-
Liang et al., 2012 [26]	68 cm	Tobii X120	video	-
Rigas et al., 2012 [31]	60 cm	CRS Eye Tracker	face images	40 s
Holland and Komogortsev, 2013 [23]	56.5 cm 68.5 cm 54 cm	Tobii TX300 Eye Link 1000 Play Station Eye	Reading, Free Viewing Moving Object, Password	-
Galdi et al., 2013 [32]	60 cm	Tobii 1750	face images	192 s
Juhola et al., 2013 [35]	Head-mounted eye tracker	EOG & VOG based devices	jumping point	EOG 80 s VOG 64 s
Cantoni et al., 2015 [5]	60 cm	Tobii 1750	face images	192 s
Rigas et al., 2015 [36]	55 cm	EyeLink 1000	jumping point, text, video	Total time 3 min and 40 s

Table 2 Database and evaluation protocol. Abbreviations: FAR – False Acceptance Rate; FRR – False Rejection Rate; EER – Equal Error Rate; ROC – Receiver Operating Characteristic curve; CMC – Cumulative Match Characteristic curve; DET - Detection Error Trade-off curve; IR – Identification Rate; H – High; M- Medium; L – Low.

Method	Database size	No. of acquisition sessions	Performance measures	Evaluation protocol	Evaluation over time
Kasprowski and Ober, 2004 [17]	9	1	FAR, FRR	H	-
Bednarik *et al.*, 2005 [18]	12	1	Accuracy	H	-
Kinnunen *et al.*, 2010 [24]	17	1	EER	M	-
Deravi and Guness, 2011 [22]	3	1	Error rate	M	-
Holland and Komogortsev, 2011 [28]	32	2	EER, ROC	L	M
Cuong *et al.*, 2012 [19]	79	1	Accuracy	M	-
Zhang and Juhola, 2012 [20]	132	1	Accuracy	M	-
Komogortsev *et al.*, 2012 [6]	59	2	Decidability index, HTER	M	L
Liang *et al.*, 2012 [26]	5	2	Accuracy	H	L
Rigas *et al.*, 2012 [31]	15	2	EER	L	L
Holland and Komogortsev, 2013 [23]	(Exp. 1) 22; (Exp. 2) 32; (Exp. 3) 28.	1	DET, EER	M	-
Galdi *et al.*, 2013 [32]	88	3	EER, ROC, CMC	M	H
Juhola et al., 2013 [35]	80	1	Accuracy	H	-
Cantoni et al., 2015 [5]	112	3	EER, ROC, CMC	M	H
Rigas et al., 2015 [36]	320	2	IR, EER, GAR	H	L

Table 3 Method description. Abbreviations: KNN – K-Nearest Neighbors; SVM – Support Vector Machines; PCA – Principal Component Analysis; FFT – Fast Fourier Transform; UBM - Universal Background Model; LDC – Linear Discriminant Analysis; OPC - Oculomotor Plant Characteristics; CEM-B - Complex Eye Movement Behavior; FDM - Fixation Density Map; MFCC - Mel Frequency Cepstral Coefficient.

Method	Acquired data	Feature extracted	Feature vector size	Classifier	No. of soft biometrics	No. of hard biometrics	Modality
Kasprowski and Ober, 2004 [17]	Jumping point coordinates, Left eye gaze coordinates, Right eye gaze coordinates	15 cepstral coefficients for each four waveforms	12288/60	KNN (for k=3 and k=7), Naïve Bayes, C4.5 Decision Tree and SVM	0	0	static
Bednarik et al., 2005 [18]	Pupil Diameters, Distance between the reflections, Velocities, Delta pupil diameters	FFT, PCA, FFT+PCA.	-	KNN	2	0	dynamic
Kinnunen et al., 2010 [24]	XY Coordinate	histogram of angles	-	UBM with maximum likelihood	0	0	dynamic
Deravi and Guness, 2011 [22]	XY Coordinate, Interocular distance, Pupil diameter	XY Coordinate, Interocular distance, Pupil diameter	11250	KNN, SVM, LDC and Fisher Classifier	1	0	static
Holland and Komogortsev, 2011 [28]	XY Coordinate	saccade, fixation, scan path based features	-	Gaussian Cumulative Distribution Function	0	0	dynamic
Cuong et al., 2012 [19]	XY Coordinate, Eye Difference, Eye Velocity	MFCC	12288	Decision Tree, KNN, Bayesian Network, and SVM	0	0	dynamic
Zhang and Juhola, 2012 [20]	Saccades	amplitude, accuracy, latency and maximum velocity, acceleration , and deceleration	-	Multilayer perceptron (MLP) networks, SVM	0	0	dynamic
Komogortsev et al., 2012 [6]	XY Coordinate	OPC using saccades	-	T-test with voting, Hoteling's Tsquare test	0	2	dynamic
Liang et al., 2012 [26]	XY Coordinate	acceleration, geometric, muscle property	-	Neural Networks and SVM	0	0	dynamic
Rigas et al., 2012 [31]	XY Coordinate	graph representation	-	Graph Edit Distance with KNN	0	0	static
Holland and Komogortsev, 2013 [23]	XY Coordinate	saccade, fixation, scan path based features	-	Gaussian Cumulative Distribution Function	0	0	dynamic
Galdi et al., 2013 [32]	XY Coordinate, fixation duration and timestamps	gaze duration in face ROIs	17	Euclidean distance	0	0	static
Juhola et al., 2013 [35]	Saccades	amplitude, latency, accuracy, maximum velocity	-	KNN, linear and quadratic discriminant analysis, Naïve Bayes	0	0	dynamic
Cantoni et al., 2015 [5]	XY Coordinate, fixation duration and timestamps	Graph representation	1848	Frobenius norm	0	0	dynamic
Rigas et al., 2015 [36]	Fixation: start time, duration, and centroid Saccade: start time, duration, mean and peak velocity	Duration, velocity, and amplitude of the fixations and saccades	-	Multi-source weighted fusion: OPC [6], CEM-B [37], FDM [38]	0	0	dynamic

Table 4 Final results. Abbreviations: FAR – False Acceptance Rate; FRR – False Rejection Rate; EER – Equal Error Rate; AUC – Area Under ROC curve; IR – Identification Rate; EOG - Electro-oculographic; VOG - Video-oculogram; H – High; M- Medium; L – Low.

Method	Reproducibility	Novelty	Best results
Kasprowski and Ober, 2004 [17]	M	L	avg. FAR of 1.48% avg. FRR of 22.59%
Bednarik et al., 2005 [18]	H	L	Identification Rate of 90%
Kinnunen et al., 2010 [24]	L	H	EER of 28.7%
Deravi and Guness, 2011 [22]	M	L	Identification Rate of 100 %
Holland and Komogortsev, 2011 [28]	M	L	EER of 26.5%
Cuong et al., 2012 [19]	H	M	Identification Rate: Set A 93.6%; Set B 91.1%
Zhang and Juhola, 2012 [20]	L	M	Accuracy of 89%
Komogortsev et al., 2012 [6]	H	H	HTER of 19%
Liang et al., 2012 [26]	L	H	Identification Rate of 82%
Rigas et al., 2012 [31]	M	M	EER of 30%
Holland and Komogortsev, 2013 [23]	H	M	EER of 27%
Galdi et al., 2013 [32]	H	M	EER of 36%, AUC 0,66
Juhola et al., 2013 [35]	L	M	Identification Rate: VOG 93%; EOG 97%
Cantoni et al., 2015 [5]	H	H	EER of 22%, AUC 0,82
Rigas et al., 2015 [36]	H	M	EER of 5.8%; Rank-1 IR of 88.6%

6.1. Discussion

The first consideration, observing the information in Table 2, is that only 7 out of 15 approaches were tested on sufficiently wide databases (i.e. composed by more than 50 different individual) to consider the performances assessment reliable: Cuong et al., 2012 [19], Zhang and Juhola, 2012 [20], Komogortsev et al., 2012 [6], Galdi et al., 2013 [32], Juhola et al., 2013 [35], Cantoni et al., 2015 [5], and Rigas et al., 2015 [36]. Among them, the ones that obtained better performances are Cuong et al. [19], Zhang and Juhola [20], and Juhola et al. [35]. Although the optimal performance obtained, IR of 97% in the best case, and the limited acquisition time, these three methods adopted head-mounted eye trackers for data collection. The use of wearable eye trackers assures high recognition accuracy but also limits the use of eye movement recognition in context in which the user is very cooperative.

The best performing method, among those employing remote eye trackers, is Rigas et al., 2015 [36]. However, in order to obtain an IR of 88.6%, the authors used a multi-stimuli and multi-algorithm approach, requiring an acquisition process of more than 3 min. This indicates that eye movement based recognition in less constrained conditions (i.e. using remote eye trackers) still need to be improved in order to achieve performance comparable with head-mounted based approaches.

7. Comparative evaluation (Rigas et al., GAS, and GANT)

In this section we present the comparative evaluation of three methods (previously presented in section 5). We have selected in particular these three works for the following reason: the use of faces, or in general of images, as stimuli, that requires less user cooperation as the user is naturally lead to observe an image instead of following a jumping LED with his/her gaze. This could allow a wider use of this technology if we also consider that, despite other approaches that employ head-mounted eye-tracker, the gaze can be recorded at a distance. As shown in Table 1, there are only three works that employed face images as stimuli: Rigas et al. [31], Galdi et al. [32] and Cantoni et al. [5]. In the next section we present a comparative evaluation of these three methods on the same database consisting of gaze recordings from 112 subjects, in order to obtain a reliable and relevant performance assessment.

We tested the three methods on the database presented below in section 7.1. We assess algorithms' performance in terms of Receiver Operating Characteristic curve (ROC), Equal Error Rate (EER) and Cumulative Match Score curve (CMS). In the following, we describe our experiments and in Table 5 we report our results.

7.1. Database

The eye tracker employed to record eye movements is the Tobii 1750. The database consists of 112 different subjects of different ages [5]. Sixteen black-and-white face pictures were displayed. The presentation order of the 16 images was random. On average, a single test session, including task explanation and device calibration, lasted a little more than 5 min.

A first series of experiments S_1 consisted in three acquisition sessions separated in time, where 88 different subjects were acquired. A second series of experiments S_2 was repeated after one year with both new observers and observers that participated also in S_1. A total of 34 observers participated in S_2, 10 of them had been involved in S_1 as well.

An important feature of this publicly available[8] database is that it contains for each observer three (or more for those observers who participated both in S_1 and S_2) acquisitions separated in time. It is then possible to make a comparative evaluation over time of the features of the gaze plot of a certain observer in order to verify the stability over time of this biometric trait and to analyze the influence of memory (i.e. when an observer recognize a face that has already been seen in the past).

7.2. Experimental protocols

The database is composed from three rounds of acquisition separated in time. 112 persons participated in round 1, a part of them (44 persons) participated also in round 2 and, finally, 23 of them participated in round 3 too. We used round 1 as Probe set and, in turn, round 2 and round 3 as Gallery set. In this way we simulate a more challenging situation in which the system could operate in a real-life scenario, i.e., the case in which unregister users (in our experiments observers who participated only in round 1) try to get authenticated by the system.

7.3. Results for Rigas et al.

To reproduce the same kind of experiments as in [31], we used single observation as template, i.e., the sample containing the fixation points of observer *i* on the face image of subject *j*, where *i = 1, 2, …, observer-no* and *j = 1, 2, …, 16* (observer-no = 112 in round 1, 44 in round 2 and 23 in round 3). However, due to the high number of resulting comparisons (e.g. when testing round 2 vs. round 1 we have about 112x16x44x16 = 1261568 comparisons), we decided to select only the first 8 subjects among the 16 (4 females and 4 males, 4 of whom were unknown people and 4 were famous people), obtaining about 315392 comparisons in the worst case (round 1 vs. round 2). In Figure 5 and Figure 6, Cumulative Match

[8] http://biplab.unisa.it/GazeAnalysis/database/

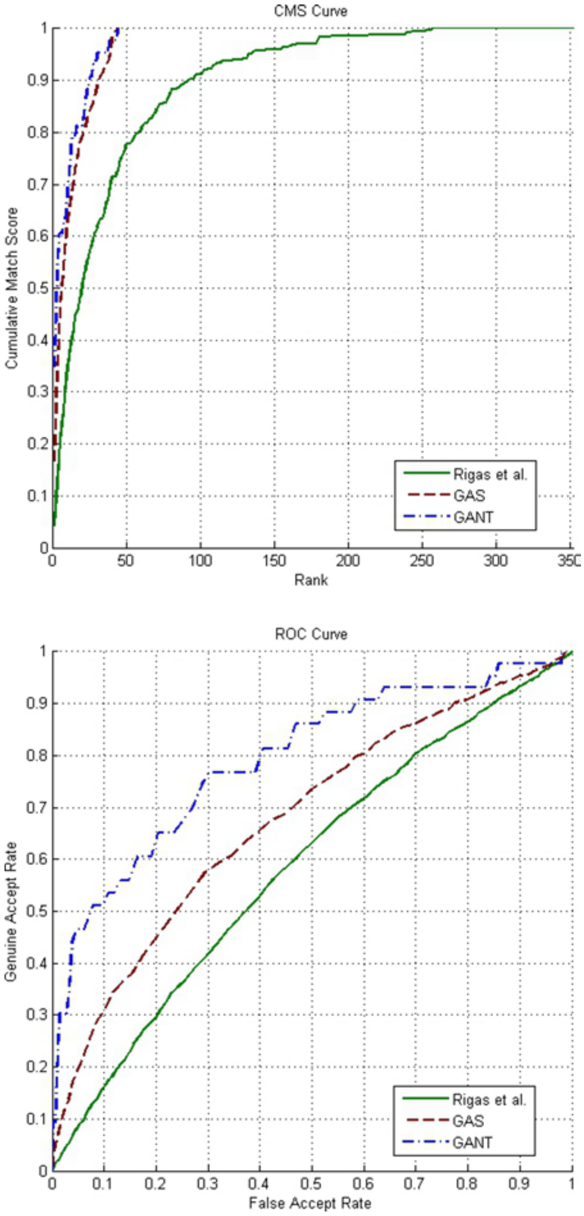

Figure 5. CMS and ROC curves for experiment 1. Results for all three methods when using Round 2 as Gallery set and Round 1 as Probe set.

Score curve (CMS) and Receiver Operating Characteristic curve (ROC) curves indicating Rigas et al. performances on our database are presented.

7.4. Results for GAS

In [32] two kinds of experiments were presented, the first one using a single feature vector as template and the second uses a fixation model, obtained by averaging, for each observer, all 16 observations coming from the Gallery set. We decided to reproduce only the second experiment that yields the best results. In Figure 5 and Figure 6 we can see the experimental results for GAS.

7.5. Results for GANT

Finally, we tested GANT using the same protocol presented in [5], we just inverted the roles of round 1 and round 2 and 3. In our experiment, as mentioned before, we used round 1 as Probe set and round 2 and 3, in turn, as Gallery set, in order to simulate the attempt of unregister users to access the system. In Figure 5 and Figure 6 present results obtained by GANT.

The best performance and by far is obtained using GANT (see Table 5). From the computational point of view, Rigas et al. approach came out to be the most expensive one. To compare two observations, the algorithm requires building a minimum spanning tree (MST) starting from the set of fixation points. When the number of fixation points increases, the time needed to build the MST significantly affects performance.

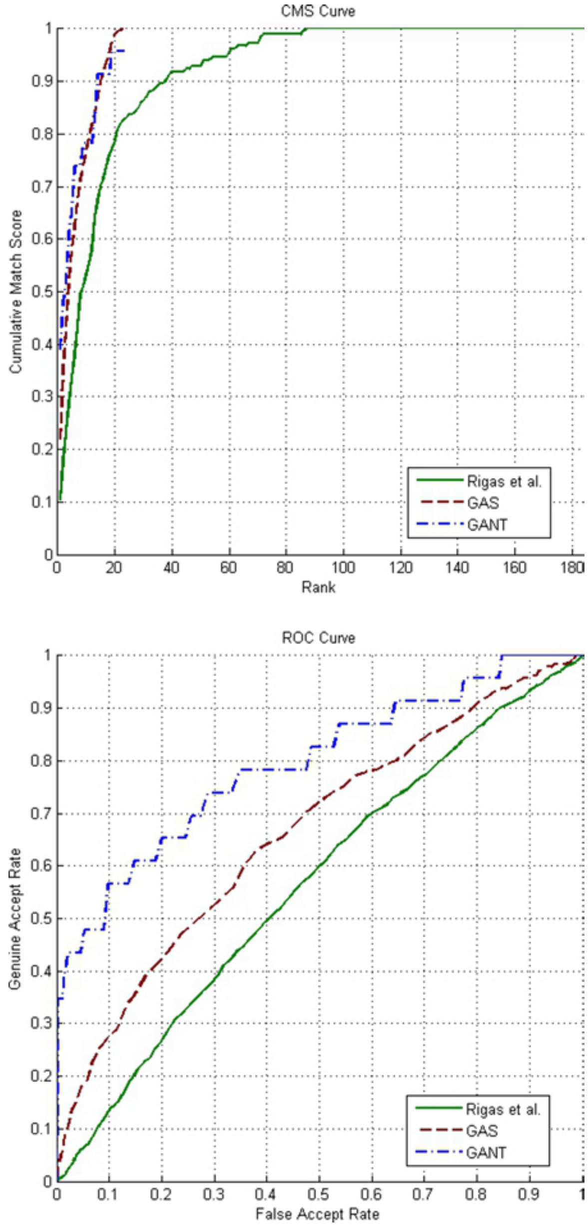

Figure 6. CMS and ROC curves for experiment 2. Results for RIGAS, GAS, and GANT using Round 3 as Gallery set and Round 1 as Probe set.

Table 5. Experimental Results.

Experiment	**EER**	**AUC**	**CMS(1)**
Rigas et al. round 2 vs. round 1	0.4322	0.5869	0.0429
Rigas et al. round 3 vs. round 1	0.4504	0.5651	0.1033
GAS round 2 vs. round 1	0.3685	0.6788	0.1593
GAS round 3 vs. round 1	0.3755	0.6621	0.2120
GANT round 2 vs. round 1	0.2719	0.7932	0.3488
GANT round 3 vs. round 1	0.2739	0.7930	0.3913

8. Gaze analysis - quo vadis

Kasprowski et al. [33] have reported the results for the first eye movement verification and identification competition held in conjunction with BTAS 2012. They provide background, discuss previous research, and describe the datasets and methods used in the competition. The results highlight the importance of careful eye positional data capture to ensure meaningful identification outcomes and proper evaluation, on one side, and warn of the dangers associated with recording of not calibrated eye positional data, on the other side. Best identification result for the Kaggle competition, with scores standing for log loss, and methods reported, was achieved using Random Forests and LDA.

Otherwise, the scores for rank-1 identification accuracy, varied in the range from 58.6% to 97.7% depending on the dataset and methods employed for identification. The best result (95%) on data set B, the hardest by far in terms of number of subjects (75) and recordings (4,168), was achieved using 2D histogram speed and direction and SVM.

Concerning GANT vs. top of the line BTAS 2012 performer, there are some important aspects worth to discuss. For the competitions held in conjunction with BTAS2012 (i.e., EMVIC and EMVIC on Kaggle) 4 datasets were used captured using 2 different eye trackers: Ober2, a head mounted eye tracker (datasets A and B); Eye Link 1000, a remote eye tracker but chin resting was employed to stabilize subjects' heads during recording (datasets C and D). The stimulus used in all 4 datasets was a jumping dot.

On datasets A and B, captured with very controlled acquisition conditions, the best methods obtained an accuracy of about 95-97% but on datasets C and D, with less controlled acquisition conditions, the best methods obtained an accuracy of about 58% and 66% respectively. GANT, which is characteristic of methods using uncontrolled settings, compares favorably against the best BTAS 2012 performers operating on less controlled conditions.

In 2014, another competition “The Second Eye Movements Verification and Identification Competition” (EMVIC 2014), was held in conjunction with IJCB 2014. The dataset consisted in 1430 eye movement recordings, from 34 subjects, registered when a person observed a face picture. The capture device employed was a head-mounted JazzNovo eye tracker registering eye positions with 1kHz frequency. Surprisingly, as reported in [39] by Kasprowski and Harezlak, the best performances obtained were very low, of about 40% of correct classifications, due to the fact that the protocol adopted for the acquisition process, produced a very challenging database.

Finally, in [40] Rigas and Komogortsev, have recently reported the results of the BioEye “Competition on Biometrics via Eye Movements” held in conjunction with BTAS 2015. A total of 306 subjects participated in the collection of the database. Three acquisition sessions were carried out and the time interval between the second and the third session, in which a subset of 74 subjects was recorded, was 1 year. The eye-tracker employed was an EyeLink eye-tracker working at 1000 Hz. Chin resting was employed to stabilize subjects' heads. Only the left eye was captured. The best ranked method obtained a Rank-1 Identification Rate of about 96% by averaging the results over the jumping dot and the text reading tasks. However, the acquisition conditions were strictly controlled. The results obtained in the previous competitions, demonstrate than when using a less controlled setting for data acquisition, the performances strongly drop.

Another consideration relevant for gaze analysis is the interaction between the surface being observed and the scan paths followed by the eye. Towards that end, Filip et al. [34] provide a psychophysical analysis of human gaze attention to textured materials and its interaction with surface intrinsic characteristics. The findings reported revealed several interesting facts. First, a shaped textured surface is definitely more attractive to look at and more informative for observer than a flat textured surface, which receives only half of the fixations in comparison with the shaped surface. Second, average local variance of a curved surface texture can predict observers’ gaze attention to both texture and its underlying geometry. In other words, the higher the frequencies and regularities present in the material texture, the easier identification of possible differences becomes with a lower number of shorter fixations. Third, angular degradation of view and illumination is material dependent and less apparent in comparison with a very subtle data spatial smoothing. Finally, upper parts of stimuli receive generally more attention mainly at the beginning of the trial, with observers tending to seek information in horizontal and vertical directions with more attention. The immediate application of such findings is for effective perceptually driven attention, compression, and rendering of texture data in virtual and mixed-reality applications.

9. Conclusions

This paper reviews gaze analysis methods and makes the case for using them for biometric identification when active, behavioral, and dynamic biometrics are warranted. State-of-the art gaze analysis methods are reviewed and compared according to a wide set of proposed criteria. A second contribution of this paper consists in the comparative evaluation of three methods (Rigas et al., GAS, and GANT) tested for the first time on a common database that consists of human faces stimuli, and with GANT shown to perform by far the best. The potential for further improvements and applications is considered as well. Performance improvement should come from richer stimuli including task dependent user profiles, while applications could go much beyond identification to include medical care and rehabilitation, privacy, marketing, and education.

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