

Biometric Authentication via Complex Oculomotor Behavior

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Abstract

This paper presents an objective evaluation of previously unexplored biometric techniques utilizing patterns identifiable in complex oculomotor behavior to distinguish individuals. Considered features include: saccadic dysmetria, compound saccades, dynamic overshoot, and express saccades. Score-level information fusion is applied and evaluated by: likelihood ratio, support vector machine, and random forest. The results suggest that it is possible to obtain equal error rates of 25% and rank-1 identification rates of 47% using score-level fusion by likelihood ratio.

1. Introduction

Identity is often defined as “the state of having unique identifying characteristics held by no other person or thing” [1]. Biometrics, then, is the rigorous study and application of those aspects of identity that may be measured and quantified. With initial investigations tracing as far back as the mid-19th century [2], the field of biometrics has grown to encompass a myriad of physical and behavioral traits [3], from fingerprints and facial structure, to speech and handwriting.

Over the past decade, study of the human visual system has shown that eye movements may be utilized to uniquely identify individuals in a biometric context [4-7]. Consisting of both physical and neurological components [8], and due to the minute scale, the accurate replication of eye movements outside of a living subject is practically infeasible, providing inherent levels of counterfeit-resistance and liveness detection that many traditional biometrics cannot [9].

Further, eye movements may be captured and processed in real-time using an unmodified camera [10] through the use of modern video-oculography techniques. Not only does this make the collection of eye movement data cheap and efficient, but the ability to capture iris patterns [11] and eye movements [5] with a single sensor allows for easy integration into multi-modal biometric systems.

Though still in its infancy, the field of eye movement biometrics is growing rapidly. In the span of a short few years, it has been shown that eye movement biometrics: can be easily incorporated into multi-modal systems to increase the recognition accuracy [12]; provide an inherent level of liveness detection and counterfeit-resistance [13]; are largely stimulus independent [14], and therefore do not require complex data collection procedures; and can be readily combined utilizing simple information fusion techniques [6].

1.1. Previous Research

“The human visual system exhibits several types of basic oculomotor behavior in response to various stimuli. In the field of human-computer interaction, fixations and saccades are of primary interest. Fixations occur when the eye globe is held in a relatively stable position, providing heightened visual acuity. Saccades occur when the eye globe rotates quickly between points of fixation. The term scanpath refers to the spatial path formed by a sequence of fixations and saccades.” [14]

Initial investigations of eye movements as a behavioral biometric began in 2004, when Kasprowski and Ober [5] examined the first 15 cepstral coefficients of the positional signal (a technique common in speech recognition) using naïve Bayes classifiers, C4.5 decision trees, SVM polynomials, and KNN ($k = 3$ and $k = 7$).

Silver and Biggs [7] followed in 2006, applying a probabilistic neural network to combine keystroke biometrics with higher-level eye movement features, including: fixation count, the 8 most significant fixations, mean fixation duration, mean saccade velocity, mean saccade duration, and mean vertical position.

More recently, in 2011, Holland and Komogortsev [4] examined a wider range of eye movement features, including: fixation count, average fixation duration, average vectorial saccade amplitude, average horizontal saccade amplitude, average vertical saccade amplitude, average vectorial saccade velocity, average vectorial saccade peak velocity, velocity waveform indicator, scanpath length, scanpath convex hull area, mean-shift regions of interest, inflection count, amplitude-duration coefficient, and amplitude-peak velocity coefficient.

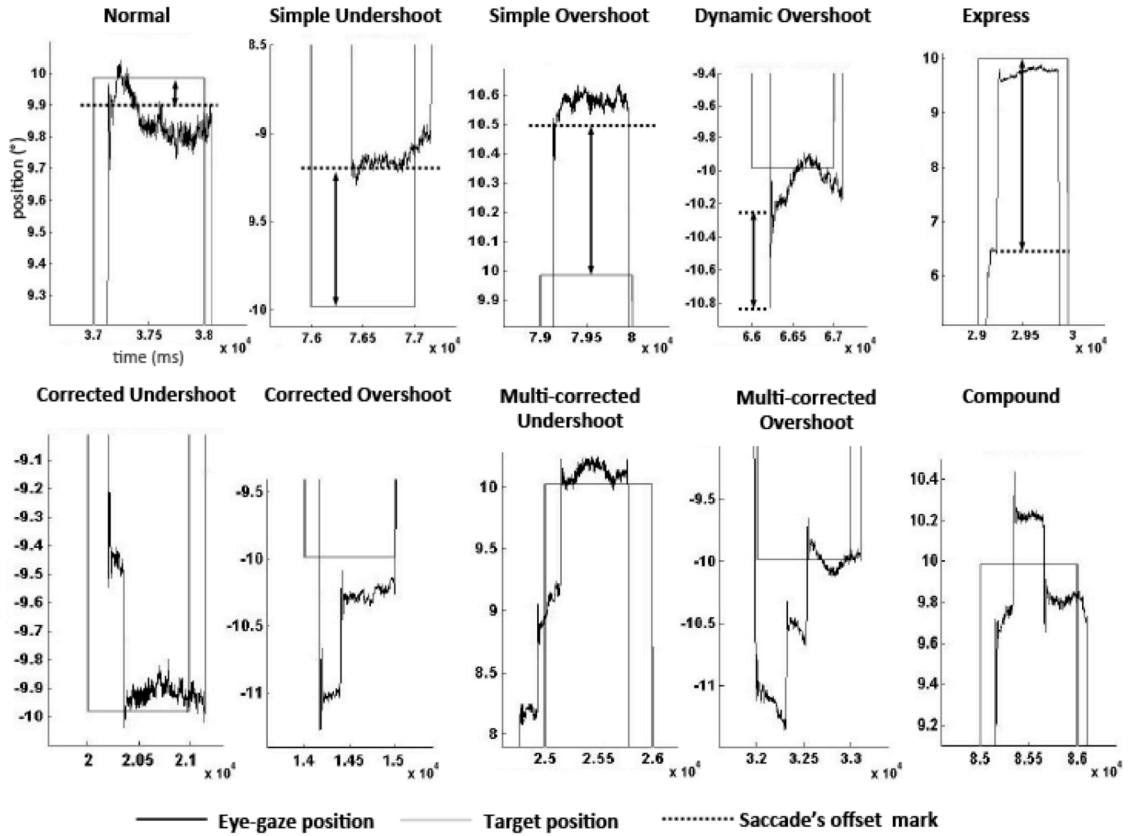


Figure 1: Complex Oculomotor Behavior (x-axis = time in milliseconds; y-axis = position in degrees). Arrows represent distance thresholds to accommodate detection of individual COB.

Komogortsev et al. [6] considered the fusion of complex eye movement patterns (CEM) and oculomotor plant characteristics (OPC) to enhance biometric accuracy. The OPC techniques makes use of the saccadic eye movement signal to estimate the physical properties of the eye according to a mathematical model of human eye movements [15]. The combination of CEM and OPC biometrics provided a roughly 30% increase in authentication accuracy compared to the accuracy of individual techniques.

1.2. Motivation & Hypothesis

While it has been shown that eye movements are applicable as a behavioral biometric, the error rates obtained by existing techniques have been less than ideal, and fail to measure up to well performing biometric techniques. In a multi-modal biometric system, the poor error rates of existing eye movement biometrics might leave the system open to zero-effort attacks, assuming successful spoofing of the other employed modalities. As such, it is our goal to investigate techniques that improve the overall accuracy of eye movement biometrics, to improve the reliability and counterfeit-resistance of these techniques. Further, as a relatively unexplored branch of the biometric field, there are yet many untested aspects of the human visual system that can be employed for the biometric purposes.

We hypothesize that complex oculomotor behavior (subconscious corrective behaviors exhibited by the human visual system) can be utilized to uniquely identify a given individual. In examining this hypothesis we evaluate several previously unexplored forms of complex oculomotor behavior, including: saccadic dysmetria, compound saccades, dynamic overshoot, and express saccades. We proceed to investigate common information fusion techniques as applied to these features, including score-level fusion by: likelihood ratio, linear support vector machine, and random forest.

2. Complex Oculomotor Behavior

We define complex oculomotor behavior as a subtype of basic oculomotor behavior (fixations and saccades). Complex oculomotor behavior involves variant forms of basic oculomotor behavior, often indicating novel or abnormal mechanics. In the current paper, we consider the various forms of saccadic dysmetria, compound saccades, dynamic overshoot, and express saccades.

Saccadic dysmetria is a common occurrence, in which a saccade undershoots or overshoots the target stimulus [8]. Often, if the dysmetria is too large, these saccades are followed by one or more small corrective saccades in the direction of the target. We identify the type of dysmetria based on these characteristics: undershoot, overshoot, simple (uncorrected), corrected (1 corrective saccade), and multi-corrected (2 or more corrective saccades).

Undershoot and overshoot are identified simply by the relation of the fixation centroid to the target stimulus, where a fixation below the target is identified as undershoot and a fixation above the target is identified as overshoot. These are further classified as corrected or multi-corrected based on the number of fixations that occur during the presentation of the target stimulus.

Compound saccades (also referred to as macrosaccadic oscillations [8]) occur as a series of dysmetric saccades around a target. As such, we may identify compound saccades as a series of two or more corrective saccades occurring during a single stimulus, in which the direction of movement changes (undershoot-overshoot-undershoot, overshoot-undershoot-overshoot, etc.).

Dynamic overshoot occurs as a small (0.25° to 0.5° amplitude), oppositely directed, post-saccadic corrective movement [8]. In the current work, the data points that describe these post-saccadic movements are typically merged with the preceding saccade. As such, we identify dynamic overshoot by projecting the absolute distance travelled during the saccade onto the centroid of the previous fixation; if the projected centroid exceeds the post-saccade fixation centroid by more than 0.5° (corresponding to a minimum overshoot of 0.25°), we may assume that dynamic overshoot occurred.

Express saccades have an abnormally quick reaction time between the appearance of a stimulus and the onset of the saccade [8]. Boch and Fischer [16] found that regular saccades have a typical latency of 150 milliseconds; as such, we identify saccades with latency less than 150 milliseconds as express saccades.

3. Methodology

Existing eye movement datasets, collected by Komogortsev et al. [14, 17], were utilized for comparative evaluation, with collection methodology presented in the following subsections.

3.1. Apparatus & Software

Eye movements were recorded using an EyeLink 1000 eye tracking system [18], with a sampling rate of 1000 Hz, spatial accuracy of 0.5° , average calibration accuracy of 0.7° (SD = 0.5°), and average data validity of 66% (SD = 36%). A chin rest was employed to improve stability, and stimuli were presented on a flat screen monitor positioned at a distance of 685 millimeters from each subject, with screen dimensions of 640×400 millimeters, and screen resolution of 2560×1600 pixels. SVM^{light} [19], an open source implementation of Vapnik’s Support Vector Machine [20], was utilized for SVM-based fusion, all other algorithms and analysis were implemented and performed in MATLAB, and run using a 3.1 GHz quad-core CPU with 16 GB memory (DDR3 RAM).

3.2. Participants

Eye movement recordings were collected for a total of 32 subjects (26 male / 6 female), ages 18 – 40 with an average age of 23 (SD = 5.4). For each stimulus, 29 of the subjects performed 4 recordings each, and 3 of the subjects performed 2 recordings each, generating a total of 122 unique eye movement recordings per stimulus.

3.3. Procedure

Each subject generated four eye movement recordings for each of two distinct stimuli. The first two recordings for each subject were conducted during the same session with a 20-minute break between recordings; the second two recordings were performed a week later, again with a 20-minute break between recordings.

The stimuli employed a technique commonly used to evoke a fixed-amplitude saccade at regular intervals [8]. A single white dot jumps back and forth on a plain black background, eliciting a saccade for each jump. One stimulus was designed to evoke 30° horizontal saccades, and the other to evoke 20° vertical saccades. These distances were chosen due to screen constraints, and the complications associated with separating low-amplitude saccades (less than 1°). Subjects were instructed to follow the white dot with their eyes, with 100 saccades elicited per recording.

Eye movement recordings are parsed to remove invalid data points. Recordings are stored in an eye movement database, with each record linked to the stimulus, subject, and session that generated the recording. The recordings are then processed and classified into fixations and saccades using an eye movement classification algorithm [21], followed by micro-saccade and micro-fixation filters respectively. The initial classification algorithm classifies individual data points with a velocity greater than $20^\circ/\text{sec}$ as belonging to a saccade, with all remaining points belonging to fixations. The micro-saccade filter re-classifies saccades smaller than 0.5° amplitude as fixations, and the micro-fixation filter re-classifies fixations of less than 100 milliseconds as saccades. Fixation and saccade groups are then merged, identifying fixation and saccade-specific features.

Complex oculomotor behavior is identified from the fixations and saccades of each recording based on the criteria presented in Section 2, with algorithm thresholds defined according to the relevant literature. Eye movement recordings are partitioned into training and testing sets, and biometric match scores are generated by comparing the amount of each complex oculomotor behavior present in pairs of recordings using a Gaussian CDF normalized to a scale of the unit interval, where x and μ are the metric values being compared and σ is the metric-specific standard deviation within the training set:

$$p = 1 - \left| \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^x e^{\frac{t-\mu}{2\sigma^2}} - 1 \right| \quad (1)$$

Common information fusion techniques including likelihood ratio, linear support vector machine, and random forest are applied to the match scores generated across the different metrics to generate a single match score for each pair of recordings. Error rates are then calculated on the testing set for individual metrics and fusion techniques under biometric verification and identification scenarios.

Under the verification scenario, each record in the testing set is compared to every other record in the testing set exactly once, and error rates are calculated from these comparisons. Under the identification scenario, every record in the testing set is compared to every other record in the testing set, and identification rates are calculated from the largest match score(s) from each of these comparison sets.

4. Results

Eye movement recordings were partitioned into training and testing sets, by subject, according to a uniformly random distribution, with 50% of recordings placed in the training set and 50% of recordings placed in the testing set. The results presented in the following subsections are averaged over 20 random partitions.

4.1. Match Score Distribution

The distribution of genuine and imposter match scores were smoothed with a kernel smoothing density estimate and average across all random partitions. Under ideal circumstances, genuine match scores would have a distinctly different distribution than the imposter match scores of a given algorithm; however, for all COB features there was very little separability. To conserve space, and due to the high similarity of match score distributions, match score distributions are given for a single representative COB feature in Figure 2.

4.2. Randomness & Entropy

To assess the stability of biometric matching, Kolmogorov-Smirnov tests for uniformity and normality and Wald-Wolfowitz runs tests for randomness were applied to the match scores generated for each metric. As well, Shannon entropy was calculated as a measure of information density.

For reference, randomness and entropy values were averaged over 1000 iterations for 1000 uniformly and normally distributed random numbers. For uniform random numbers:

- Kolmogorov-Smirnov test for uniformity: $p = 0.5021$
- Kolmogorov-Smirnov test for normality: $p < 0.0001$
- Wald-Wolfowitz runs test for randomness: $p = 0.5247$
- Shannon entropy = 7.8019

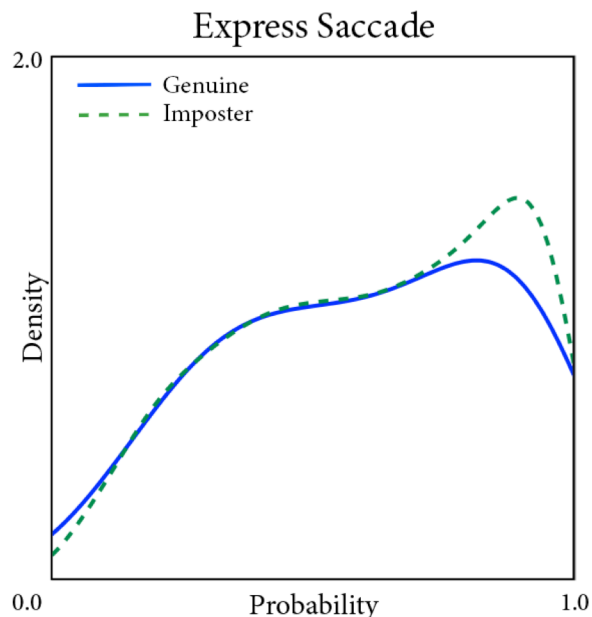


Figure 2: Representative Match Score Distribution.

For normal random numbers:

- Kolmogorov-Smirnov test for uniformity: $p < 0.0001$
- Kolmogorov-Smirnov test for normality: $p = 0.4996$
- Wald-Wolfowitz runs test for randomness: $p = 0.5079$
- Shannon entropy = 3.9496

In all cases, biometric match scores were distinctly non-uniform and non-normal, with $p < 0.0001$. Table 1 presents Wald-Wolfowitz runs probability and Shannon entropy for each metric.

Metrics	Runs		Entropy	
	<i>H</i>	<i>V</i>	<i>H</i>	<i>V</i>
<i>Simple Undershoot</i>	0.00	0.00	4.94	5.15
<i>Simple Overshoot</i>	0.00	0.00	5.00	4.72
<i>Corrected Undershoot</i>	0.00	0.00	5.27	5.09
<i>Corrected Overshoot</i>	0.00	0.00	4.69	4.41
<i>Multi-Corrected Undershoot</i>	0.00	0.36	3.69	3.60
<i>Multi-Corrected Overshoot</i>	0.00	0.07	2.02	2.75
<i>Compound Saccade</i>	0.00	0.00	4.40	4.35
<i>Dynamic Overshoot</i>	0.00	0.03	6.00	6.33
<i>Express Saccade</i>	0.00	0.00	5.39	5.40
Information Fusion				
<i>Likelihood Ratio</i>	0.00	0.48	4.79	4.78
<i>Support Vector Machine</i>	0.00	0.04	0.81	0.82
<i>Random Forest</i>	0.03	0.29	5.00	4.97

Table 1: Randomness & Entropy.

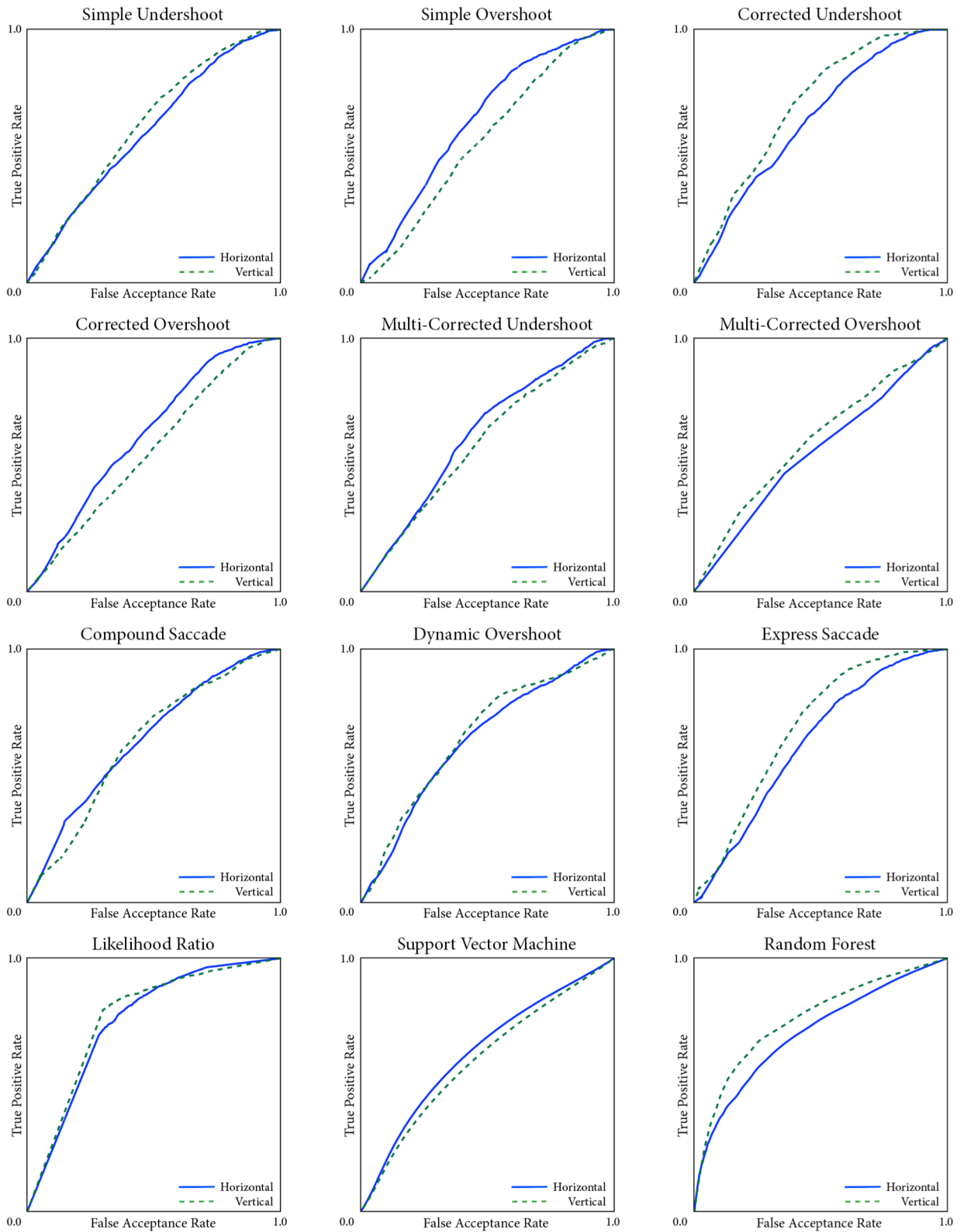


Figure 3: Receiver Operating Characteristic.

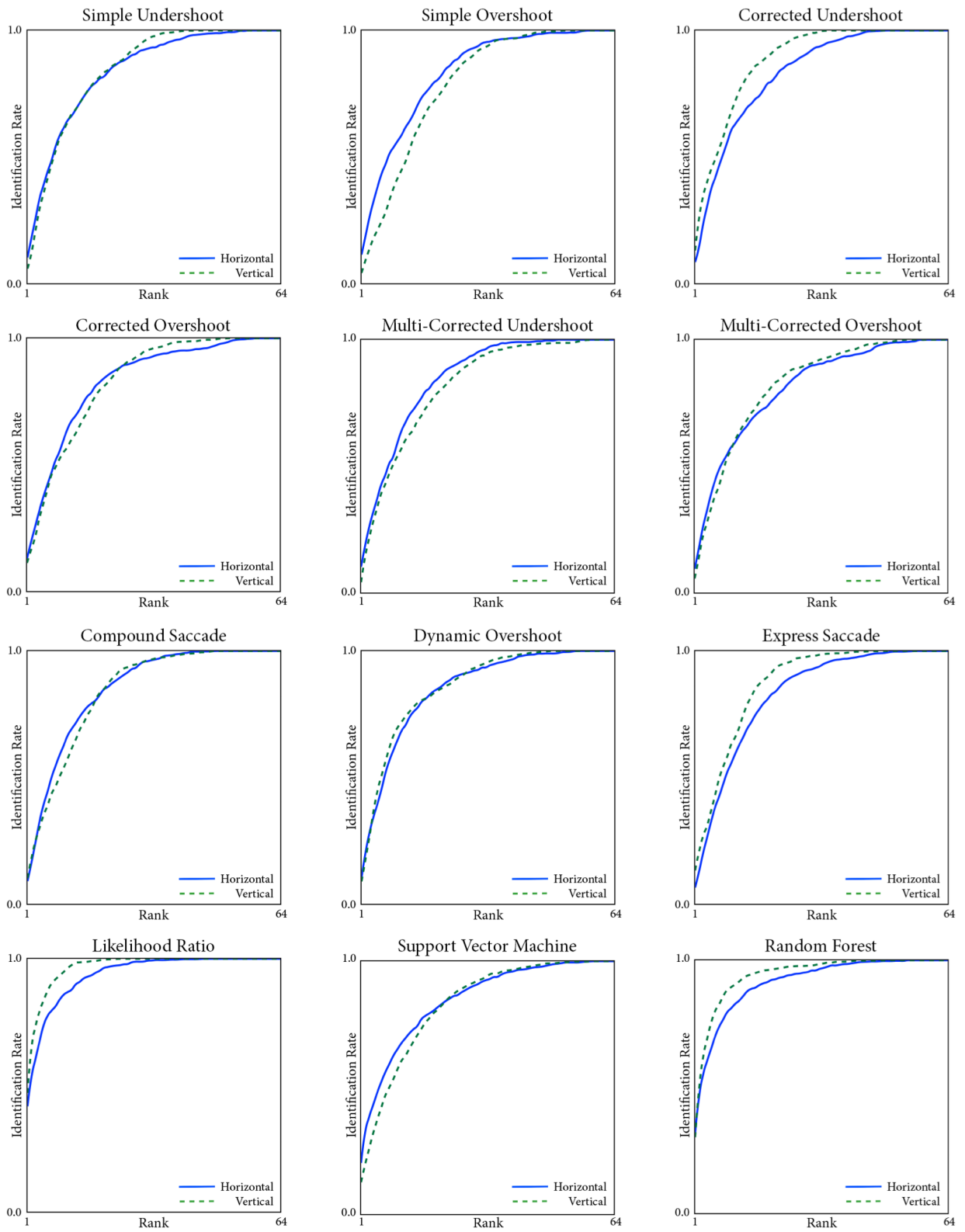


Figure 4: Cumulative Match Characteristic.

4.3. Verification Scenario

False acceptance rate (FAR) is defined as the rate at which imposter match scores exceed the acceptance threshold, false rejection rate (FRR) is defined as the rate at which genuine match scores fall below the acceptance threshold, and true positive rate (TPR) is defined as the rate at which genuine match scores exceed the acceptance threshold. The equal error rate (EER), shown in Table 3, is the rate at which false acceptance rate and false rejection rate are equal, and the receiver operating characteristic (ROC), shown in Figure 3, plots true positive rate against false acceptance rate.

<i>Metrics</i>	<i>Horizontal</i>	<i>Vertical</i>
<i>Simple Undershoot</i>	43%	39%
<i>Simple Overshoot</i>	39%	45%
<i>Corrected Undershoot</i>	40%	35%
<i>Corrected Overshoot</i>	42%	46%
<i>Multi-Corrected Undershoot</i>	40%	43%
<i>Multi-Corrected Overshoot</i>	49%	43%
<i>Compound Saccade</i>	39%	38%
<i>Dynamic Overshoot</i>	38%	38%
<i>Express Saccade</i>	39%	35%
<i>Information Fusion</i>		
<i>Likelihood Ratio</i>	29%	25%
<i>Support Vector Machine</i>	45%	45%
<i>Random Forest</i>	35%	30%

Table 3: Equal Error Rates.

4.4. Identification Scenario

Identification rate (IR) is defined as the rate at which enrolled subjects are successfully identified as the correct individual, where rank-k identification rate is the rate at which the correct individual is found within the top k matches. The rank-1 identification rate, shown in Table 4, is the rate at which the correct individual has the highest match score, and the cumulative match characteristic (CMC), shown in Figure 4, plots identification rate by rank, for all ranks.

<i>Metrics</i>	<i>Horizontal</i>	<i>Vertical</i>
<i>Simple Undershoot</i>	10%	6%
<i>Simple Overshoot</i>	11%	4%
<i>Corrected Undershoot</i>	8%	13%
<i>Corrected Overshoot</i>	13%	11%
<i>Multi-Corrected Undershoot</i>	10%	4%
<i>Multi-Corrected Overshoot</i>	9%	6%
<i>Compound Saccade</i>	9%	10%
<i>Dynamic Overshoot</i>	10%	9%
<i>Express Saccade</i>	6%	13%
<i>Information Fusion</i>		
<i>Likelihood Ratio</i>	42%	47%
<i>Support Vector Machine</i>	20%	13%
<i>Random Forest</i>	32%	30%

Table 4: Rank-1 Identification Rates.

5. Discussion

It should be noted in advance that the relatively small subject pool employed in the current paper makes it difficult to conduct a detailed analysis of the considered methods; however, the database size is similar to those employed in existing eye movement biometric research, and we feel that it is sufficient to draw general conclusions.

From the Kolmogorov-Smirnov tests for normality and uniformity, it is apparent that the match scores generated for each metric are effectively non-random. Despite this, however, the Wald-Wolfowitz runs test indicated a degree of randomness in multi-corrected vertical dysmetria, which appears to have propagated to both likelihood ratio and random forest fusion. In this case, it is likely that there was a low amount of multi-corrected vertical dysmetria across all recordings, due to the reduced saccadic amplitude enforced by screen constraints. Further, low Shannon entropy in multi-corrected dysmetria and support vector machine fusion indicates a large degree of match score clustering in these metrics.

The match score distributions offer several insights of particular interest. It is immediately obvious from the match score distributions that there is very little separation between genuine and imposter match score distributions for any of the considered metrics, with a tendency for the density of genuine scores to peak at a lower match score than imposter scores.

From a biometric standpoint, this is less than ideal, as it indicates that, on their own, none of these metrics are particularly useful as biometric indicators. From a physiological standpoint, however, it is interesting to note that there is a higher degree of similarity in the amount of complex oculomotor behavior performed by different subjects than in repeated recordings from a single subject. This suggests that the degree of complex oculomotor behavior exhibited by normal subjects has a tendency to either increase or decrease naturally in a manner that is stable across the recorded population.

Looking at error rates under both verification and identification scenarios largely confirms the conclusions already drawn from match score distributions; that is, on their own, the metrics considered for complex oculomotor behavior provide little viability as biometric indicators. Yet, the information fusion of COB features provides accuracy on par with existing eye movement biometrics [4, 5, 7, 15]. While these techniques are not yet accurate enough to be useful in a standalone system, eye movement biometrics have already been employed to improve the accuracy and liveness-detection of multi-modal systems [12], providing an error reduction of 19% over a purely iris-based system.

Strangely, and perhaps counter-intuitively, information fusion by likelihood ratio outperforms all other techniques by a substantial margin. Likelihood ratio fusion constructs

Gaussian mixture models of genuine and imposter match score distributions in n-dimensional feature space within the training set, and produces a single match score for each feature vector by calculating the ratio of the genuine PDF over the imposter PDF. At first glance, we might attribute this to separability in n-dimensional space, but this is unlikely given the poor performance of the linear support vector machine.

It is our opinion that this accuracy is achieved primarily due to the multivariate nature of Gaussian mixture models. This would suggest that while there are not obvious differences in the amount of complex oculomotor behavior produced by individual subjects, there are distinctive patterns in the way that these behaviors change in relation to each other.

6. Conclusion

This paper has presented an objective evaluation of previously unexplored biometric techniques utilizing patterns identifiable in complex oculomotor behavior to distinguish individuals. Saccadic dysmetria, compound saccades, dynamic overshoot, and express saccades were evaluated for their efficacy as biometric indicators, and score-level information fusion was applied and evaluated by: likelihood ratio, linear support vector machine, and random forest.

While the error rates achieved by the considered techniques cannot compete with existing biometric standards, the results indicate that it is possible to identify subjects in a biometric context through the analysis of complex oculomotor behavior. Through score-level fusion by likelihood ratio, the application of complex oculomotor behavior achieved an equal error rate of 25% and rank-1 identification rate of 47%. As such, it is likely that the combination of COB with existing eye movement biometrics, such as CEM and OPC, would provide even greater performance.

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