

DEVELOPMENT, EVALUATION, AND ANALYSIS
OF COMPLEX EYE MOVEMENT BIOMETRICS

by

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ABSTRACT

Eye movements present a novel and unique solution to the challenges faced by modern biometrics. Consisting of both physical and neurological components, and due to the minute scale, the accurate replication of eye movements outside of a living subject is practically infeasible (if not impossible), providing an inherent level of liveness detection and counterfeit-resistance. Further, recent advances in video-oculography allow for the efficient capture of eye movements from even low-quality image sensors, reducing the cost of entry and enabling integration with many existing iris, periocular, and facial recognition systems.

The following thesis describes the development of biometric techniques for the automated identification of human subjects based on patterns of eye movements that occur naturally during directed viewing of a visual stimulus. The proposed techniques are then evaluated according to standard practices in the biometric field to assess performance under varying environmental conditions. The results of this evaluation are analyzed to provide recommendations for suitable applications of the described techniques and direction for future research in this area.

1. INTRODUCTION

Biometric authentication refers to the automated process of extracting, processing, and comparing physical or behavioral traits for the purposes of identifying an unknown identity or verifying a claimed identity [1]. Biometrics has earned a crucial role in the fields of law enforcement, criminal justice, and corporate and personal security. Suspect identification, criminal conviction, access restriction, and personalized interfaces constitute only a small subset of the applications of biometrics in modern society.

The systematic collection of physical or behavioral characteristics for the purposes of identification dates as far back as 1858, with the collection of handprints to identify workers [2], and has since expanded to include such features as: fingerprints [3], iris patterns [4], signature [5], and speech [6]. As technology advances, however, biometric traits are becoming easier to reproduce, circumventing the purposes of biometric authentication techniques and leaving gaps in the efficacy of the systems that use them [7]. To combat this, improvements must continue to be made to existing biometric systems to increase the accuracy and specificity of biometric authentication techniques.

There are two primary usage scenarios for biometric authentication [1], shown in Figures 1 and 2. Biometric verification is a 1-to-1 comparison, in which an individual's biometric template is compared against the existing (enrolled) template of a claimed identity; in many ways this is similar to using a password to log-in to a computer or website. Biometric identification is a 1-to-many comparison, in which an individual's biometric template is compared against all of the enrolled templates in a database, and the identity of the closest match is returned; this can be related to the typical search engine.

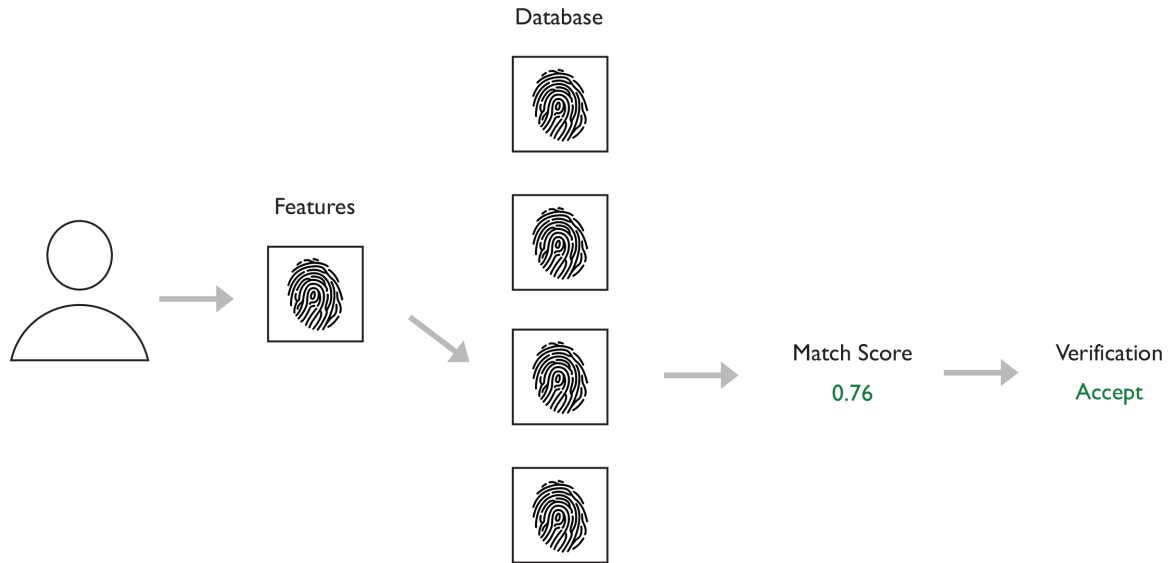


Figure 1. Biometric Verification.

In a verification scenario, there are a number of metrics typically associated with biometric accuracy. False acceptance rate is defined as the rate at which impostor match scores exceed the acceptance threshold, false rejection rate is defined as the rate at which genuine match scores fall below the acceptance threshold, and true positive rate is defined as the rate at which genuine match scores exceed the acceptance threshold. The equal error rate is the rate at which false acceptance rate and false rejection rate are equal. In this scenario, biometric accuracy is typically evaluated by equal error rate [1], where a lower equal error rate indicates a higher accuracy.

In an identification scenario, there is typically only one metric that is considered, the identification rate. Identification rate 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. In this scenario, biometric accuracy is typically evaluated by the rank-1 identification rate [1]; that is, the rate at which the correct individual has the highest match score.

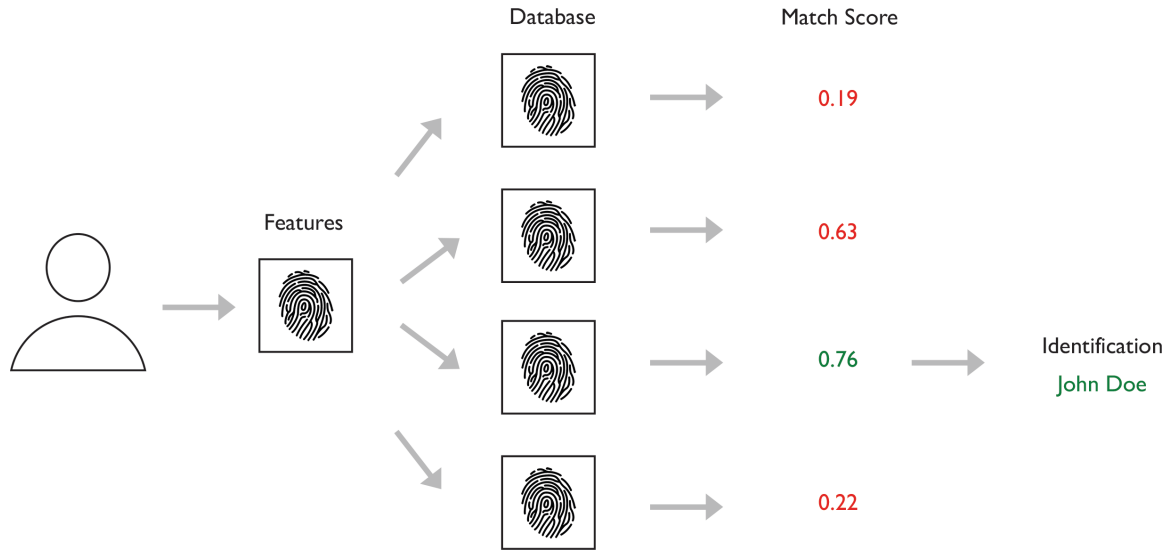


Figure 2. Biometric Identification.

There are a number of factors that must be considered when implementing an automated biometric system: accuracy, counterfeit-resistance, speed, and cost. For example, a human observer might review facial photographs with perfect accuracy, but too slowly to be considered useful; or, a fingerprint scanner may be implemented with acceptable accuracy and speed, but be easily fooled by duplicate images.

Biometric Authentication

The human face is one of the most distinctive features with which we assign and recognize identity in our daily lives, and its overall structure is largely dependent on the physical structure of the human visual system. Facial geometry was first proposed as a biometric trait in the 1960s [8], but did not begin to gain traction with the biometric community until the 1990s [9]. Early research in this area was highly susceptible to aging effects [10, 11] and environmental factors [12], such as angle and lighting; however, recent developments have made significant progress in eliminating these issues [13].

Today, there are many techniques for performing facial recognition, which may be broadly described by two categories: those that compare geometric features of the face, and those that compare statistical features of the image [1]. Techniques in the former category, such as elastic bunch graph matching [14], typically model salient features of the face, such as the nose, mouth, and eyes; while techniques in the latter category, such as tensor factorization [13], apply mathematical transformations and analysis to the individual pixels of the facial image.

Fingerprints are often regarded as the gold standard of biometric accuracy [1], with open dataset competitions showing equal error rates approaching 2% under the effects of skin distortion and rotation [3]; however, fingerprint biometrics suffer from two major drawbacks. First, and most notably, fingerprints are easy to forge; and while fingerprint biometrics provide substantial resistance to zero-effort attacks, it takes minimal effort to defeat such a system [15]. Second, fingerprint biometrics are intrusive; that is, in order for biometric features to be collected, an individual must physically interact with the biometric sensor.

Speculation about the identifying characteristics of iris patterns can be traced as far back as the late 1800s [16], but was largely ignored in a biometric context until the 1980s, when an unfortunate patent [17] stifled innovation for nearly a decade. The study of iris pattern biometrics picked up quickly however [18], and was achieving authentication accuracies that rival fingerprints [3] by the early 2000s [19]. Unfortunately, like fingerprints, iris pattern biometrics are easily fooled by minimal-effort attacks [20].

Much of the current work in this area is based on the principles of Daugman's research [21], in which the iris pattern is projected onto a Gabor wavelet, and compared

with a test for statistical independence. Often it is necessary to correct for orientation and occlusions, but even still these techniques are highly efficient, with computation times measurable in milliseconds on modern hardware [22].

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 [23, 24]. Consisting of both physical and neurological components [25], and due to the minute scale, the accurate replication of eye movements outside of a living subject is practically infeasible (if not impossible), providing inherent levels of counterfeit-resistance and liveness detection that many traditional biometrics cannot [26].

Further, eye movements may be captured and processed in real-time using an unmodified camera [27] 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 and eye movements with a single sensor allows for easy integration into multi-modal biometric systems [28].

Human Visual System

The oculomotor plant encompasses the primary physical components of the human visual system [29], shown in Figure 3, and is composed of the eye globe, six extraocular muscles, surrounding tissues, ligaments, tendon-like components, and viscous fluids. The extraocular muscles include: the lateral and medial recti, responsible for horizontal rotation; the superior and inferior recti, responsible for vertical rotation; and the superior and inferior obliques, responsible for torsional rotation.

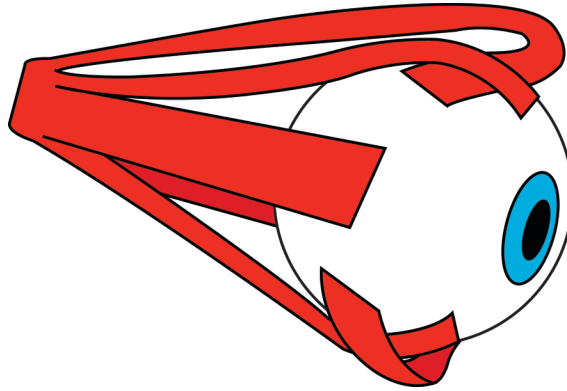


Figure 3. Oculomotor Plant.

When considered as a cohesive system, each component adds specific properties to the mechanics of the whole [25]. The extraocular muscles provide the forces required to rotate the eye globe, with opposing muscle pairs performing mutually exclusive roles of agonist and antagonist, where the agonist muscle contracts and pulls the eye globe, and the antagonist muscle expands to resist the pull. Each extraocular muscle is composed of both thin and thick filaments that cause a strict dependence between the force exerted by a muscle and its length/velocity of contraction. The eye globe provides inertia to the system, along with the resistive properties of the surrounding tissue and ligaments [30].

The brainstem control, shown in Figure 4, describes the complex network of neurological components that signal the extraocular muscles to expand and contract [25]. It should be noted that the term brainstem control is based on early modeling of the human visual system, whereas eye movements are generated by components throughout the brain, not isolated to the brainstem itself. These components include sub-regions of the thalamus, superior colliculus, and posterior parietal cortex [31], where: the thalamus is responsible for engaging visual attention; the superior colliculus is responsible for relocating visual attention; and the posterior parietal cortex is responsible for disengaging visual attention.

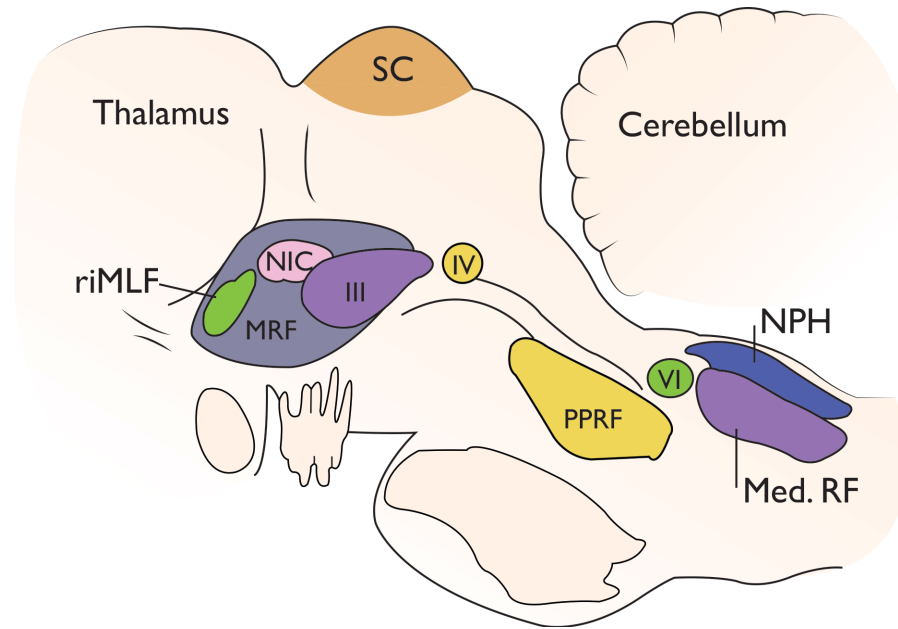


Figure 4. Brainstem Control.

The oculomotor plant, driven by the neuronal control signal, primarily exhibits six eye movement types [25]. Fixation occurs when the eye globe is held in a relatively stable position to provide high visual acuity on a fixed point; saccades occur when the eye globe rotates rapidly between points of fixation, with little visual acuity maintained during rotation; smooth pursuit occurs when the eye globe rotates slowly, maintaining fixation on a slowly moving point; optokinetic reflex refers to the sequence of smooth pursuit and saccadic eye movements which occur when the eye attempts to maintain a fixation on a rapidly moving point; vestibule-ocular reflex refers to the corrective eye movements which occur to maintain a fixation on a stationary point during head movement; and vergence refers to the corrective eye movements which occur to maintain a fixation on a point whose distance changes, without horizontal or vertical motion.

Of the various eye movement types, fixations and saccades are of particular interest in the field of human-computer interaction, as they are simple to evoke, measure, and identify on a stationary screen. These eye movements are affected not only by the physical structure of the oculomotor plant, but also by the frequency characteristics of the neuronal control signal and its speed of propagation.

At a higher level of abstraction, learned behaviors and subconscious memory mechanisms are involved in the coordination of eye movements over time, as evidenced by the inhibition of return and scanpath theory phenomena. Inhibition of return refers to the marked tendency to avoid re-fixation on previously examined features during visual search, effecting both oculomotor programming and target detection [32], while scanpath theory describes the phenomenon in which individuals tend to repeat certain scanpath trajectories during repeated viewings of a given pattern [33].

Eye Movement Biometrics

Human eye movements are representative of the cognitive strategies employed by the brain throughout the guidance of visual search, and are directly influenced by the anatomical properties of the eye, the neurological properties of the brain, conscious thought processes, and subconscious memory mechanisms [25, 31]. A number of biometric techniques have been devised over the past decade that take advantage of different aspects of human eye movements to differentiate individuals.

The foundations of eye movement biometrics stem from early research in scanpath theory, where the term scanpath refers to the spatial path formed by an ordered sequence of fixations and saccades. In 1971, Noton and Stark [33] found that the scanpath formed by a subject during the initial viewings of a pattern was repeated in 65%

of subsequent viewings. Further, it has been found by various sources that the scanpath produced for a given stimulus pattern tends to vary from person to person [34, 35]. These inherent properties of scanpaths—subconscious reproduction, variation by subject, and variation by stimulus—provide a basis for the use of eye movements as a behavioral biometric.

To the best of our knowledge, Kasrowski and Ober [24, 36] were the first to investigate the use of eye movements as a behavioral biometric, in 2004. Applying techniques commonly used in voice recognition [37], they examined the first 15 cepstral coefficients of the positional eye movement signal, using Bayes classifiers, C4.5 decision trees, polynomial support vector machines, and k-nearest neighbor ($k = 3$ and $k = 7$). On a dataset of 9 subjects, the described techniques achieved an average 1% false positive rate and 23% false negative rate.

Silver and Biggs [38] followed in 2006, investigating a set of higher-level features, including: most significant fixations, fixation count, average fixation duration, average saccade velocity, average saccade duration, and average vertical position, with feature vectors combined using a neural network. On a subject pool of 21 student participants, the described techniques achieved an average 66% true positive rate and 98% true negative rate.

Holland and Komogortsev [39] began the investigation of complex eye movement patterns (CEM-P) in 2011, examining high-level and aggregate features such as: 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, regions of interest, inflection count, coefficient of the amplitude-duration relationship, and coefficient of the amplitude-peak velocity relationship. Features were compared using a Gaussian kernel and combined with a linear combination. With a subject pool of 32 participants, the considered techniques achieved an equal error rate of 27%.

Komogortsev et al. [40] made use of mathematical models of the oculomotor plant (OPC), in 2012, to extract the anatomical characteristics unique to a given individual from the observable properties of human eye movements. Feature vectors were compared between recordings using the Hotelling T2 test to obtain a measure of similarity. On a dataset of 59 subjects, the considered techniques achieved a 19% minimum half-total error rate.

Rigas et al. [41] applied graph-based matching techniques, similar to those utilized in facial recognition [14], to the positional eye movement signal in 2012, comparing minimum spanning trees with a multivariate Wald-Wolfowitz runs test. On a dataset of 15 subjects, the proposed techniques achieved a 70% rank-1 identification rate and 30% equal error rate.

Komogortsev and Holland [42] examined high-level features related to sub-conscious corrective eye movements (COB) in 2013, considering multiple types of saccadic dysmetria and express saccades. On a dataset of 32 subjects, these techniques achieved an equal error rate of 25% and a rank-1 identification rate of 47%.

Most recently, in 2013, Holland and Komogortsev [23] improved upon the complex eye movement pattern biometrics (CEM-P) originally developed in 2011 [39], describing complex eye movement behavior (CEM-B) by comparing the distribution of

fixations and saccades with statistical techniques such as the two-sample t-test, the Ansari-Bradley test, the two-sample Kolmogorov-Smirnov test, and the two-sample Cramér-von Mises test. On a dataset of 32 subjects, the proposed techniques achieved 83% rank-1 identification rate and 17% equal error rate.

State of the Art

Having existed for less than a decade [24], the field of eye movement biometrics is still in its infancy. Despite this, and perhaps because of it, the achievable accuracy and robustness has increased at an exponential rate. In just the past year, equal error rates have seen a reduction of 63%, from 27% equal error rate to 17% equal error rate, while rank-1 identification rates have seen an increase of 157%, from 53% rank-1 identification rate to 83% rank-1 identification rate.

As a behavioral – rather than physical – biometric, it is expected that eye movements may never achieve the level of accuracy afforded by physical traits, such as fingerprints and iris patterns; however, when considered in the context of behavioral biometrics, eye movements are quite promising. For example, gait recognition was proposed in the mid-1970s [43], but did not begin to achieve reasonable accuracy until the early 2000s, with equal error rates ranging from 18-25% [44] and rank-1 identification rates ranging from 30-70% [45, 46], depending largely on the angle and speed of gait. Similarly, face recognition was proposed in the 1960s [8], but was largely ignored in a biometric context until the mid-1990s [9], with early work being highly susceptible to aging effects, achieving equal error rates of 1-7% [11] and rank-1 identification rates of 80-90% [10] for images captured within a single recording session, which became dramatically reduced to equal error rates of 12-23% [11] and rank-1

identification rates of 30-60% [10] after as little as one week between enrollment and authentication.

Unfortunately, in much the same way that smudged fingerprints and off-angle facial images reduce recognition accuracy in their respective systems, the quality of the recorded eye movement signal has been shown to reduce the accuracy of eye movement biometrics [47, 48]; and in much the same way that speed of gait can affect the accuracy of gait recognition, it is unclear if the particular pattern of eye movements, invoked by a specific stimulus, has a noticeable effect on the accuracy.

2. BACKGROUND

The work presented in this thesis is the culmination of several years of research in the field of eye movement biometrics, encompassing the development of novel biometric techniques for human identification [23, 39], the construction of a modular biometric framework for testing and evaluation [23], and the release of a live biometric system for real-world use [49]. Over the past two years, the research conducted in pursuit of this thesis has improved the accuracy of eye movement biometrics from near-random to levels approaching modern face recognition.

Biometric Techniques

Complex eye movement patterns (CEM-P), proposed in 2011 [39], were originally developed as an extension of eye movement research in the field of automated usability testing [50, 51]. Eye movements provide a strong indicator for human thought processes, and the initial investigation of CEM-P was based largely on the notion that humans perceive patterns differently, and that differences in perception are reflected through variation in eye movements.

In this way, CEM-P focused on eye movement features that might give insight into conscious or sub-conscious thought. For example, prolonged fixation might indicate an increased cognitive load, as an individual takes longer to process the available information. Similarly, a series of rapid saccades might indicate difficulty locating a visual search target, as the individual scans across the visual field.

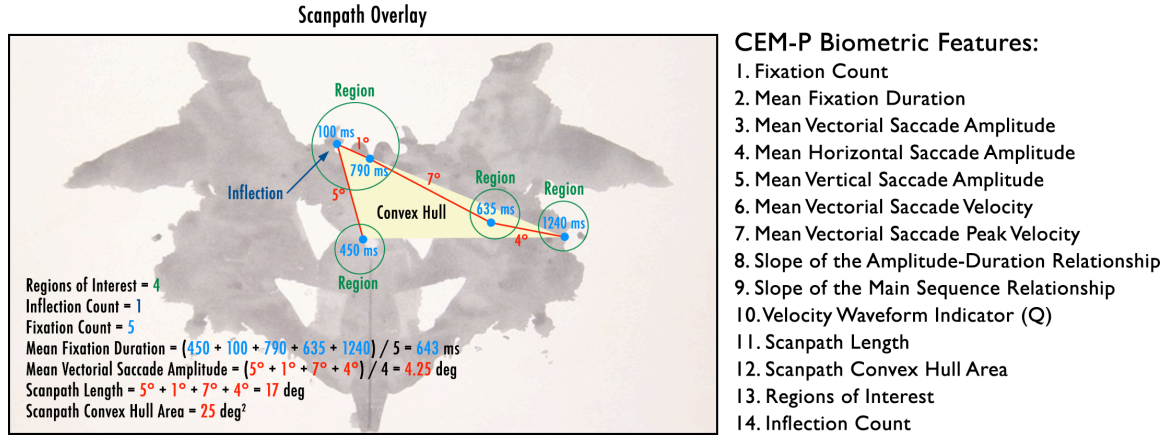


Figure 5. Complex Eye Movement Patterns (CEM-P).

To this end, a range of high-level features, illustrated in Figure 5, were selected to provide broad classification of individuals based on their eye movements. These features could be described as fitting into one of three primary categories, based on different aspects of the human visual system: fixation-based, saccade-based, and scanpath-based.

Fixation-based features include fixation count and average fixation duration. These features are most closely related to conscious thought processes, and are dependent upon the dorsal layers and rostral pole of the superior colliculus, nucleus raphe interpositus in the midline of the pons, posterior parietal cortex, and visual cortex areas V1 – V5 [52].

Saccade-based features include average vectorial saccade amplitude, average horizontal saccade amplitude, average vertical saccade amplitude, average vectorial saccade velocity, average vectorial saccadic peak velocity, slope of the amplitude-duration relationship, slope of the amplitude-peak velocity relationship, and velocity waveform indicator. These features are most closely related to sub-conscious thought processes, and are dependent upon the ventral layers of the superior colliculus,

paramedian pontine reticular formation, rostral interstitial nucleus of the medial longitudinal fasciculus, frontal eye fields, and lateral intra parietal [52].

Scanpath-based features include scanpath length, scanpath convex hull area, regions of interest, and inflection count. These features are also dependent upon the brain regions involved in fixation- and saccade-based features, and are often related to the visual search strategy employed in extracting information from a given stimulus [53].

In a biometric context, each of these features is compared using a distance function, and the distances between features are then combined using an information fusion algorithm. Previous research made use of a Gaussian kernel [54] to account for the variation typically present in physical systems, with information fusion by linear combination [55] to allow each feature to contribute to the final match score according to its accuracy.

Complex eye movement behavior (CEM-B), proposed in 2013 [23], is a natural extension of CEM-P, which attempts to address its predecessors major shortcomings. Specifically, the high-level features employed by CEM-P traded information for intuition; that is, reducing the eye movement signal to a set of average and aggregate features, while easier to visualize and understand from a human perspective, also reduced the available information that could be used to identify an individual.

In contrast, CEM-B builds on the principles of CEM-P, while reducing information loss by maintaining a focus on low-level features. Over the course of a recording, an individual will make multiple fixations and saccades. Each fixation has a start time, duration, and position on the screen, and each saccade has a start time, duration, amplitude, velocity, and peak velocity.

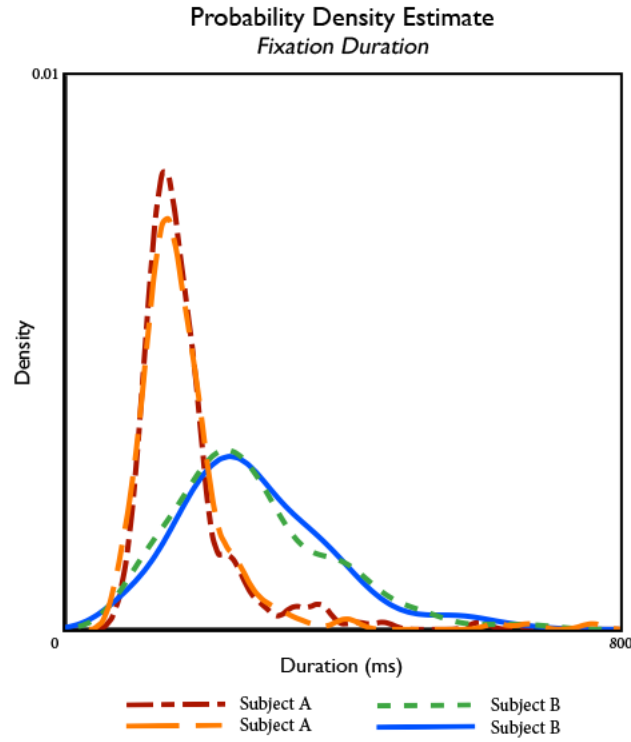


Figure 6. Complex Eye Movement Behavior (CEM-B).

In a biometric context, basic eye movement features are compared between recordings using non-parametric statistical tests on the distribution of eye movements over time, illustrated in Figure 6, with match scores for specific eye movement features (such as fixation duration) combined by information fusion. Previous research achieved the best results using a two-sample Cramér-von Mises test [56] for feature comparison, with information fusion by random forest [57].

As shown in Figure 7, the application of eye movement biometrics begins with eye tracking, recording the eye movements of a subject across a given stimulus. These eye movements are stored in a recording as a set of tuples (t, x, y) , where t is the timestamp in milliseconds, x is the horizontal gaze position in degrees of the visual angle, and y is the vertical gaze position in degrees of the visual angle. The recording is passed

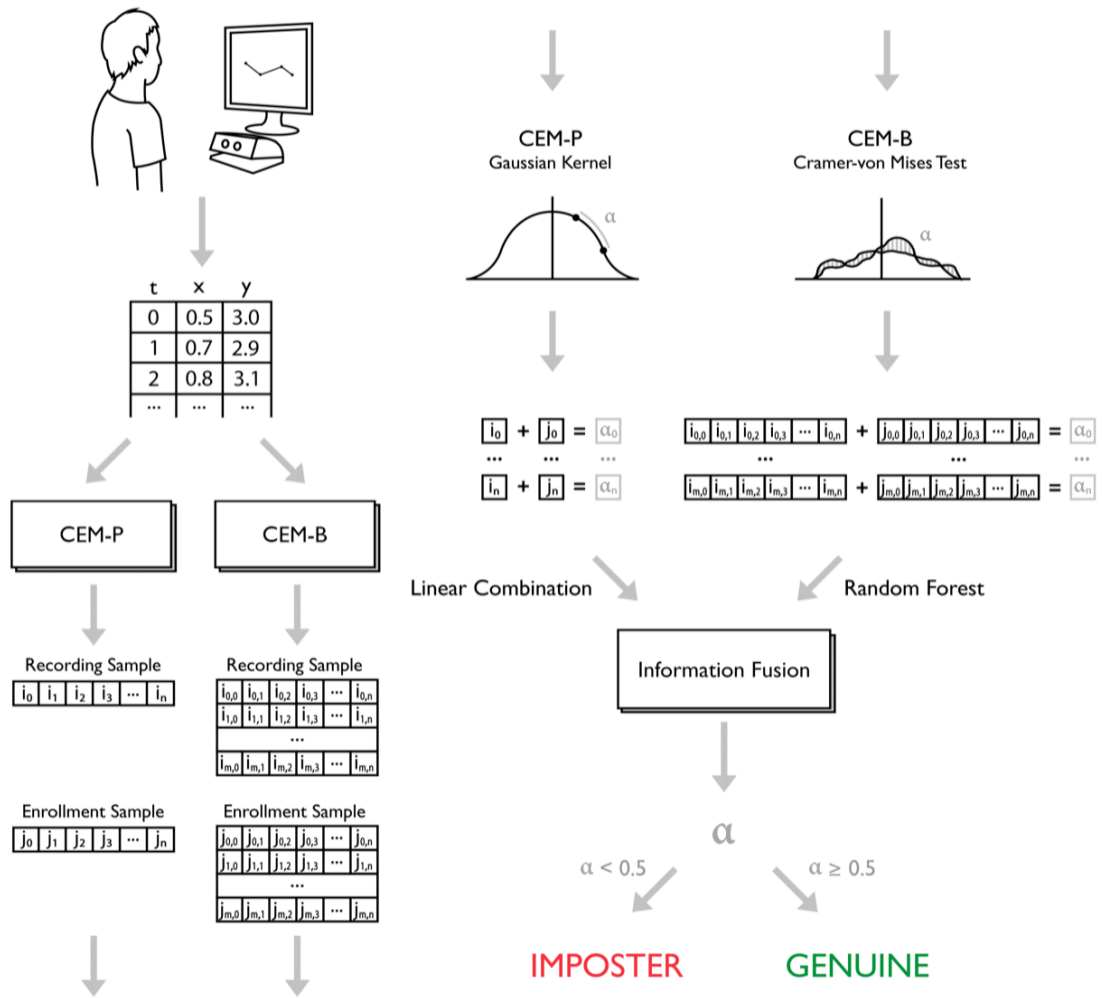


Figure 7. Eye Movement Biometrics.

to a biometric algorithm, such as CEM-P or CEM-B, for feature extraction, which produces a feature vector from the recording. The feature vector (i_0, \dots, i_n) may be single-dimensional (CEM-P) or multi-dimensional (CEM-B), and is compared to an existing feature vector (j_0, \dots, j_n) using a distance function specific to the technique to produce a set of match scores. The match scores $(\alpha_0, \dots, \alpha_n)$ produced by template matching are combined using an information fusion algorithm, to produce a single match score, α , that can be used for the purposes of biometric authentication.

Biometric Framework

In order to develop and evaluate these techniques, it was necessary to construct an extensible software framework for eye movement biometrics. Due to its comprehensive library of scientific toolkits (Symbolic Math, Statistics, Curve Fitting, etc.), simple concurrency mechanisms (parfor), and support for system modeling (Simulink), MATLAB was selected as the primary language for this framework [58].

The biometric framework was designed with modularity and concurrency in mind, and attempted where possible to employ functional programming practices (i.e. functions do not modify variables created outside of their scope). It was important that individual components could be added or modified in-place, without causing side-effects. The overall structure of the framework, shown in Figure 8, was based largely on the structure of existing biometric systems [1], which are typically comprised of the following major components: biometric sensor, feature extraction, quality assessment, biometric matching, and authentication decision.

The biometric sensor module parses individual eye movement recordings, combining available left and right eye coordinates, and removing invalid data points from the eye movement signal. This is also where dithering and downsampling occur, for examining artificial reduction in spatial accuracy and sampling rate, respectively. Eye movement recordings are stored in memory as an eye movement database, with the eye movement signal linked to the experiment, trial, and subject that generated the recording.

The feature extraction module generated feature templates for each record in the eye movement database. Eye movement features are primarily composed of fixations and saccades. The eye movement signal is parsed to identify fixations and saccades using an

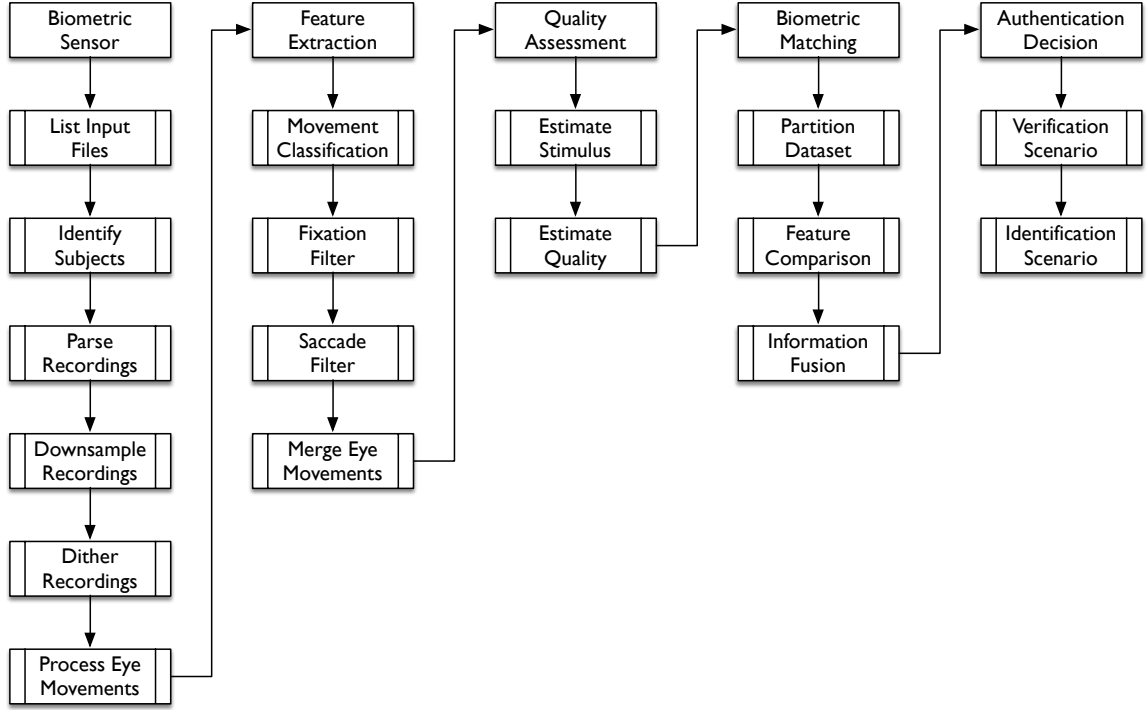


Figure 8. Biometric Framework.

eye movement classification algorithm [59], followed by micro-saccade and micro-fixation filters. The individual data points that make up each fixation and saccade are then merged, identifying fixation- and saccade-specific features.

The quality assessment module identifies the biometric viability of the generated feature templates. In this context, we utilize the fixation quantitative score, ideal fixation quantitative score, fixation qualitative score, and saccade quantitative score [60] as tentative measures of the quality of features obtained from the recording.

The biometric matching module partitions the feature templates, splitting the database into training and testing sets, by subject, according to a uniformly random distribution. Individual templates are then compared against each other, generating match scores for a given biometric technique (such as those described in the previous section, CEM-P and CEM-B). The match scores for each comparison are combined into a single

match score with an information fusion algorithm [61], with thresholds and parameters generated on the training set.

The authentication decision module calculates error rates for individual features, along with the information fusion, 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, with false acceptance rates and true positive rates calculated for all possible acceptance thresholds. 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.

Finally, an analysis module calculates various statistics used to measure different aspects of biometric performance. This includes measurements of randomness and information density (such as the Wald-Wolfowitz runs test and Shannon entropy), the distribution of match scores (normality and uniformity), and the ability of the match scores to predict similarity (overfitting and underfitting, as measured by bias and variance). The error rates calculated in the decision module are combined into a single dataset, and rational regression is performed across the entire dataset to produce an accurate model of biometric performance. Regression is performed across verification error rates to produce the parametric receiver operating characteristic, and across identification error rates to produce the parametric cumulative match characteristic [62].

Early versions of this analysis module utilized non-parametric curves for the receiver operating and cumulative match characteristics [39], with error rates averaged over multiple random partitions. While this is a common practice in biometrics literature

[1], it was determined that a more accurate representation of error rates over the population could be achieved by performing binormal regression across the error rates of all partitions, constructing a model of the population as a whole [63].

The construction of parametric receiver operating characteristics through binormal regression is a common technique in the fields of epidemiology [64], radiology [65], bioinformatics [66], and laboratory [67] and diagnostic testing [68], and has the added benefit of allowing the calculation of confidence intervals around the receiver operating and cumulative match characteristics, a statistical guarantee that the actual population model falls within a given range with a specified degree of probability. Further, this allows for the calculation of an exact equal error rate based on the equation and coefficients of the regression line, rather than estimation based on the nearest data points, providing equal error rates that are substantially more accurate.

Live Biometric System

While the biometric framework was designed to process and analyze large batches of offline eye movement recordings, it is not capable of performing biometric authentication with a live eye tracking system. Further, the MATLAB [58] environment lends itself to command-line interfaces, which are useful for developing and debugging algorithms, but impractical for real-world usage. To this end, a live biometric system was developed to interface with common eye tracking systems, provide a usable interface to the end-user, and allow real-time authentication with eye movement biometrics.

As a high-level object-oriented language, with an extensive set of standard libraries and native graphical user interface support, C# was selected as the language of choice for this project. Incidentally, many commercial eye tracking systems, such as

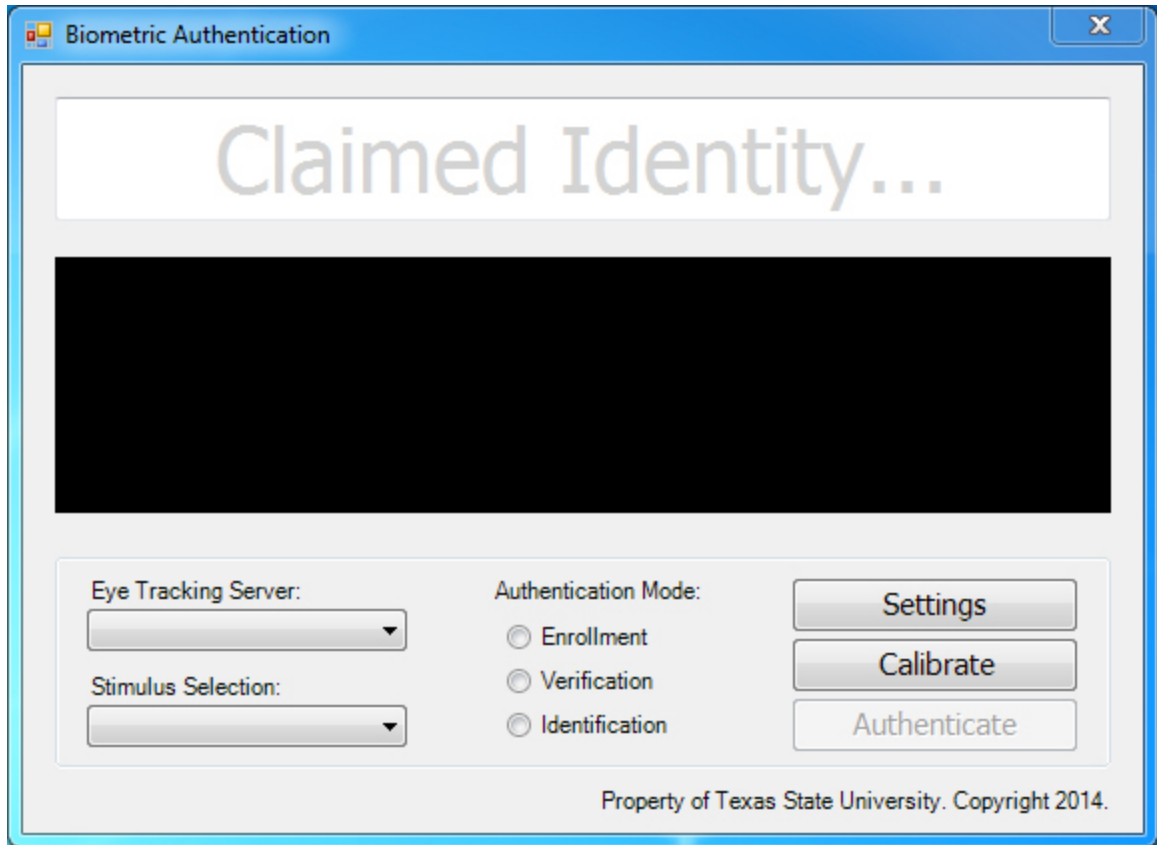


Figure 9. Live Biometric System.

those produced by Tobii [69] and EyeTribe [70], provide software development kits for C#, while support for alternative languages is mixed.

The live biometric system is composed of three major components, following roughly the model-view-controller architecture: the biometric system, the user interface, and the device wrappers. The user interface describes all forward-facing components with which the end-user may interact, the device wrappers provide a common interface for various eye tracking devices, and the biometric system contains the algorithms and procedures necessary to perform biometric authentication.

The initial user interface window, shown in Figure 9, presents the primary authentication form, through which the end-user provides a claimed identity and selects

an available eye tracking device, stimulus, and biometric modality. The authentication form provides feedback through the large status message displayed below the claimed identity textbox. The authentication form itself contains no logic, and only provides an intuitive interface to the methods exposed by the biometric system and eye tracking device wrappers.

The calibration window displays a sequential grid of stimuli, calculating the difference between the measured and predicted gaze points at each stimulus location. This procedure is necessary for most eye tracking devices to allow the system to compensate for known error. The stimulus window is generated at run-time from XML files that store the sequence and duration of stimuli. This makes it easy to add and modify the stimulus used for biometric authentication, without the need to modify and compile source code. Further, this allows the end-user to create their own stimuli, making it more difficult to prepare targeted spoof recordings, and increasing the overall flexibility and security of the system.

Despite the fact that most commercial eye tracking systems perform similar actions, and provide similar output, the hardware and software interfaces of these devices vary widely. To reduce this variability, a common eye tracking class uses reflection to identify device wrappers and list all available eye tracking devices at run-time. The end-user selects one of the available devices, and the common class uses the interface to invoke the necessary functions from the device wrapper. While this means that new device wrappers must still be incorporated at compile time, it is as simple as providing a class that maps the relevant API calls to a common interface, and does not involve modification of any existing code.

The biometric system provides the logic for the primary biometric modalities: enrollment, verification, and identification; and provides biometric comparison algorithms for the CEM-P [39], CEM-B [23], and COB [42] biometric techniques, with plans to add support for OPC [40] in the near future. Further, the biometric database used to store enrollment recordings is encrypted and compressed to improve security and reduce space requirements. For this purpose, the biometric system uses DEFLATE compression with 256-bit AES encryption. With 1.1×10^{77} possible key combinations, it is estimated that a brute-force attack against 256-bit AES encryption could take as long as 3.3×10^{56} years to crack at an operating frequency of 10.5 Petaflops (the rate of the world's fastest super-computer in 2012) [71].



Figure 10. EyeLink 1000.

3. METHODOLOGY

To examine the properties of eye movement biometrics under various environmental conditions, a series of experiments were conducted using the CEM-P [39] and CEM-B [23] biometric techniques. Eye movement recordings were collected as part of an NSF CAREER grant study, overseen by Dr. Oleg Komogortsev, and experimentation was performed using the biometric framework described in the previous section.

Apparatus & Software

Eye movements were recorded using an EyeLink 1000 eye tracking system [72], shown in Figure 10, with a sampling rate of 1000 Hz, vendor-reported spatial accuracy of 0.5° , average calibration accuracy of 0.5° ($SD = 0.2^\circ$), and average data validity of 97% ($SD = 5\%$). Stimuli were presented on a flat screen monitor positioned at 550 millimeters, with dimensions of 474×297 millimeters, and screen resolution of 1680×1050 pixels.

In all cases, the pupil was illuminated by an infrared LED to improve eye tracking accuracy, and a chin rest was employed to improve stability, as shown in Figure 11. Stimulus presentation was consistent across all recordings. All algorithms and data analysis were implemented and conducted in MATLAB [58], and run using a 3.5 GHz quad-core CPU with 16 GB memory.

Participants

Eye movement data was collected for a total of 335 subjects (178 male, 157 female), ages 19 – 46 with average age of 22 ($SD = 4$). 322 of the subjects performed 2 recordings for each stimulus, 1 of the subjects performed 1 recording for each stimulus, and 12 of the subjects were unable to produce usable recordings, for a total of 323



Figure 11. Recording Setup.

subjects and 645 unique eye movement recordings per stimulus. Texas State University's institutional review board approved the study, and all subjects provided informed consent.

Stimulus Design

The horizontal pattern stimulus made use of a technique typically employed in eye movement research to evoke a fixed-amplitude horizontal saccade at regular intervals [25]. A small white dot jumped back and forth across a plain black background, eliciting a saccade for each jump. The distance between jumps was set to correspond to 30° of the visual angle, due in part to screen constraints, complications separating low-amplitude saccades (less than 1°), and variation in the dynamics of high-amplitude saccades (greater

than 50°). Subjects were instructed to follow the white dot with their eyes, with 100 horizontal saccades elicited per session, and 2 recording sessions per subject.

The random pattern stimulus was similar in presentation to the horizontal pattern stimulus. A small white dot jumped across a plain black background in a uniformly distributed random pattern, eliciting a saccade for each jump. Subjects were instructed to follow the white dot with their eyes, with 100 randomly directed oblique saccades elicited per session, and 2 recording sessions per subject.

The textual pattern stimulus made use of various excerpts from Lewis Carroll's poem [73], "The Hunting of the Snark." The poem was chosen for its difficulty and nonsensical content, forcing readers to progress slowly and carefully through the text. Textual excerpts were selected to ensure that reading required approximately 1 minute, line lengths and the difficulty of materials was consistent, and learning effects did not impact subsequent readings. Subjects were given different textual excerpts for each recording session, with 2 recording sessions per subject.

Experimental Procedure

Eye movement recordings were generated for three distinct stimulus patterns: horizontal, random, and textual. Eye movement recordings were parsed and processed to remove invalid data points. Recordings were stored in an eye movement database, with each record linked to the stimulus, subject, and session that generated the recording. Dithering and downsampling were applied (exclusively) to the eye movement recordings to artificially reduce spatial accuracy and sampling rate for the best performing stimulus. The recordings were then classified into fixations and saccades using an eye movement classification algorithm [59].

A velocity threshold algorithm (I-VT) with documented accuracy [60] was employed to classify individual data points with a velocity greater than $20^\circ/\text{sec}$ as belonging to a saccade, with all remaining points belonging to fixations. A micro-saccade filter re-classified saccades with amplitude less than 0.5° as fixations, followed by a micro-fixation filter which re-classified fixations with a duration less than 100 milliseconds. Manual inspection was conducted on a subset of recordings to ensure the accuracy of this classification scheme.

Eye movement recordings were partitioned into training and testing sets, by subject, according to a uniformly random distribution; such that all recordings from half of the subject pool of a given dataset appeared in the training set, with the other half of the subject pool in the testing set, and there was no subject overlap between training and testing sets. Error rates were calculated under biometric verification and identification scenarios for 20 random partitions of training and testing sets. Binormal regression was performed on the error rates achieved across all partitions, using the MATLAB Curve Fitting toolbox, to generate parametric receiver operating characteristic and cumulative match characteristic curves.

Biometric template matching followed the published methods for complex eye movement behavior (CEM-B) [23] and complex eye movement pattern (CEM-P) [39] techniques. In the case of CEM-B, we utilize the two-sample Cramér-von Mises test for comparison, with information fusion by 50-tree random forest. In the case of CEM-P, we utilize a Gaussian kernel for comparison, with information fusion by linear combination.

Performance Measures

The primary concern of these experiments is to measure biometric accuracy under varied environmental factors; the most succinct measures of biometric accuracy are the equal error rate, rank-1 identification rate, and area-under-curve of the receiver operating and cumulative match characteristics. While the equal error rate and rank-1 identification rate provide a point-measure of the achievable accuracy of biometric verification and identification, respectively; area-under-curve provides a measure of biometric accuracy across the range of possible usage scenarios.

4. RESULTS

For each experiment, recordings were partitioned into training and testing sets by subject, according to a uniformly random distribution. With half of the subject pool in the training set, and half of the subject pool in the testing set, without overlap. Regression was performed on biometric error rates over 20 random partitions, and 95% confidence intervals were calculated for each regression. Error bars in relevant figures indicate the 95% confidence interval for the regression of error rates.

An equal error rate of 0% represents perfect verification accuracy, where an equal error rate of 50% is equivalent with random chance; a rank-1 identification rate of 100% represents perfect identification accuracy, with a rank-1 identification rate of $1/N$, where N is the maximum rank, representing random chance; area-under-curve of 100% represents perfect authentication accuracy in both biometric scenarios, with area-under-curve of 50% representing random chance.

The Effects of Stimulus Type

To examine the effects of stimulus on biometric accuracy, three different stimulus patterns were presented to each subject. Eye movements were recorded for the horizontal, random, and textual stimulus patterns described in the previous section, each of which exercises different aspects of the human visual system. Biometric performance measures under the verification scenario are presented in Figure 12, with identification scenario presented in Figure 13.

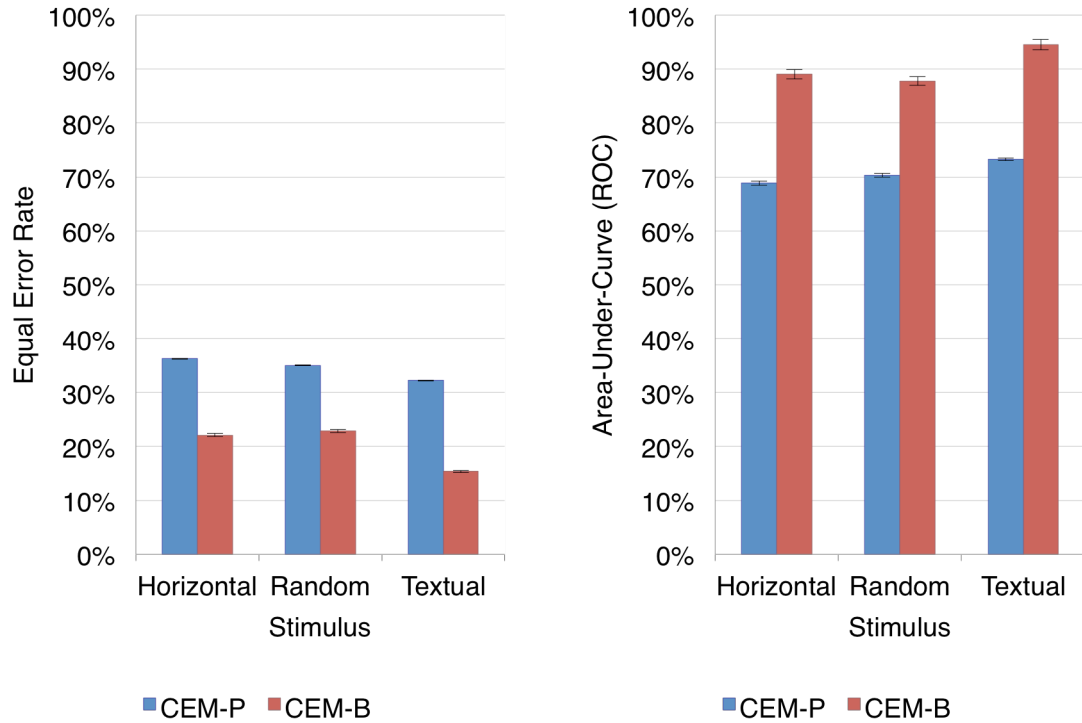


Figure 12. Stimulus Type (Verification).

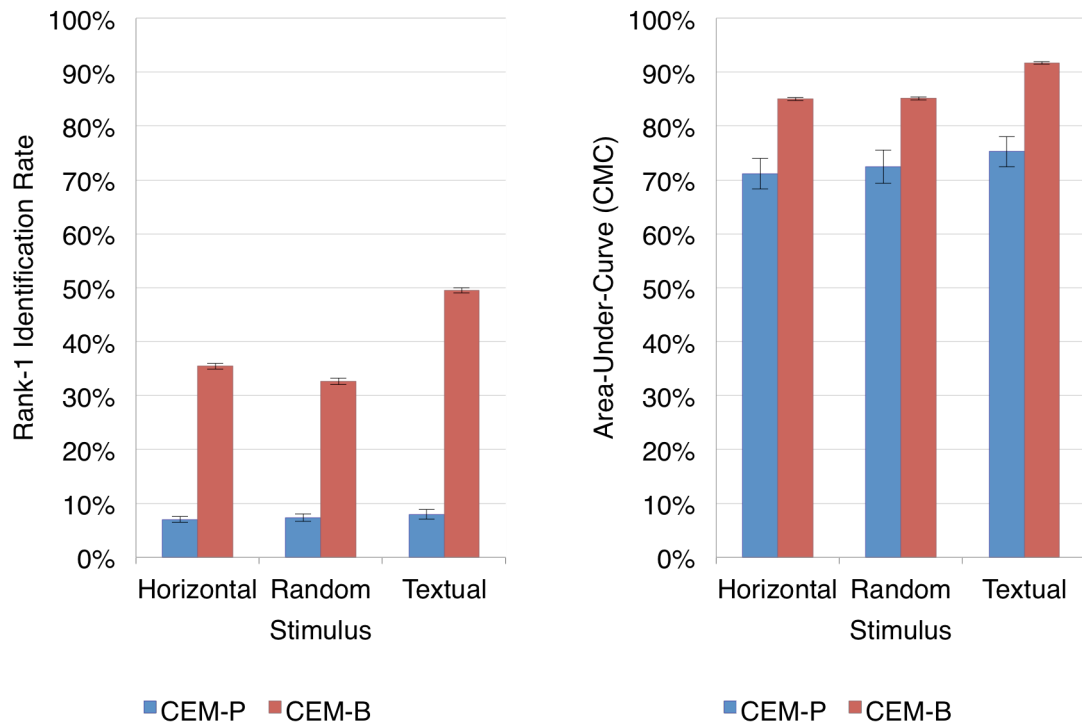


Figure 13. Stimulus Type (Identification).

While the horizontal and random stimuli provided similar accuracy, the textual stimulus provided a slight, but clear, advantage. This is likely due to the flexibility of the stimulus; without a fixed target, subjects are able to progress at their own speed. Further, there are a number of eye movement patterns that are unique to reading tasks [34, 35, 74, 75], which may contribute to this variation. Overall, the differences in accuracy attributable to stimulus are minor, and can likely be ignored for practical purposes.

The Effects of Sampling Rate

To examine the effects of sampling rate on biometric accuracy, downsampling was applied to the recordings for the textual stimulus prior to eye movement classification. Downsampling reduced the sampling rate by removing data points to lower the average time between points; considered sampling rate tiers from a hardware base of 1000 Hz include: 1000 Hz, 500 Hz, 250 Hz, 120 Hz, 75 Hz, and 30 Hz. Biometric performance measures under the verification scenario are presented in Figure 14, with identification scenario presented in Figure 15.

The sampling rate of the eye tracking system appears to have a cliff-and-plateau effect on the biometric accuracy of eye movements. There is a noticeable increase in biometric accuracy going from 30 Hz to 75 Hz, and a much more gradual increase from 75 Hz to 250 Hz, after which biometric accuracy remains largely unchanged. This seems to indicate that, while sampling rates less than 75 Hz should be avoided, anything above 75 Hz should provide reasonable accuracy, with no discernable increase in accuracy beyond 250 Hz.

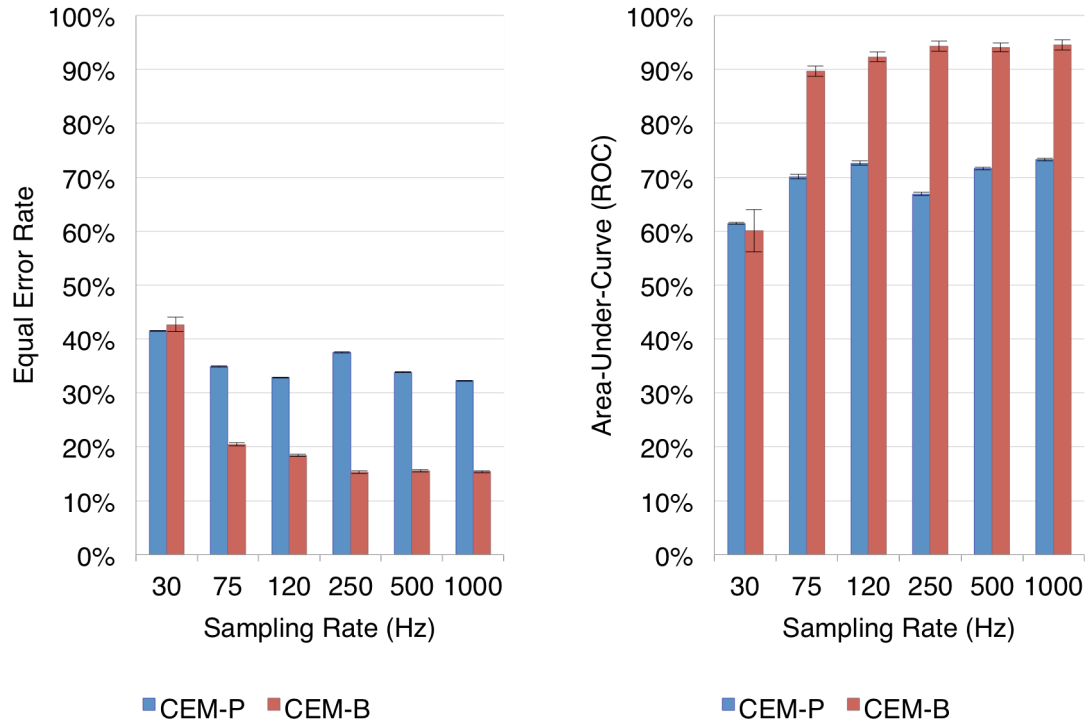


Figure 14. Sampling Rate (Verification).

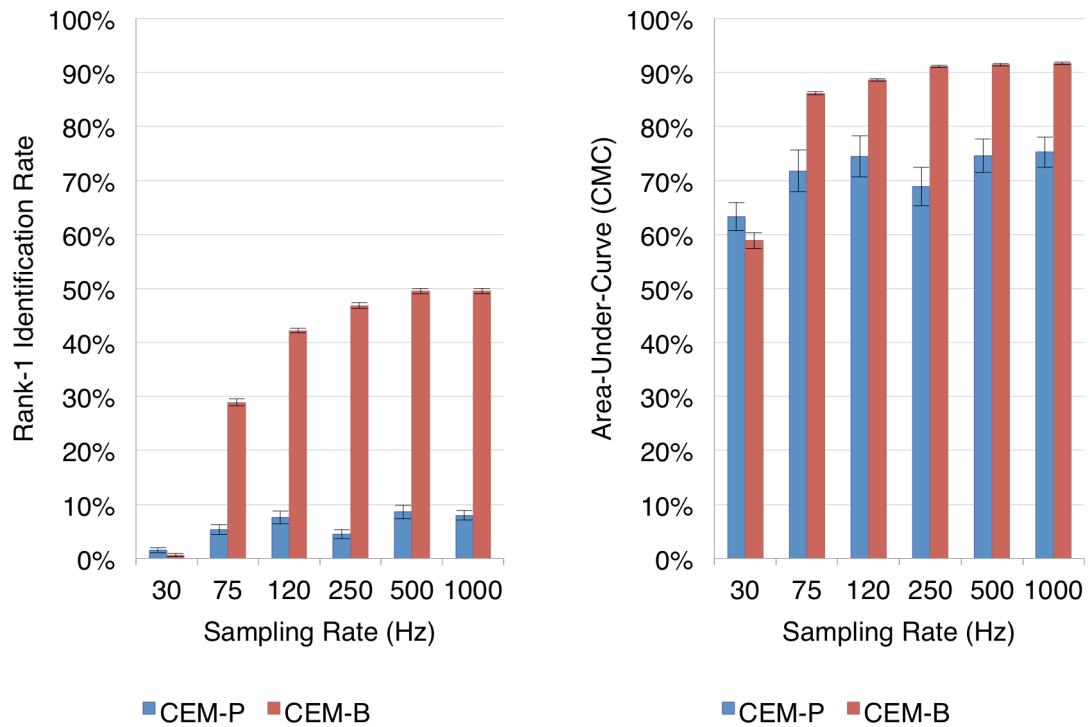


Figure 15. Sampling Rate (Identification).

The Effects of Spatial Accuracy

To examine the effects of spatial accuracy on biometric accuracy, dithering was applied to recordings for the textual stimulus prior to eye movement classification. Dithering reduced spatial accuracy by adding uniformly distributed error to the recorded eye movement position; considered spatial accuracy tiers from a hardware base of 0.5° include: 0.5° , 0.6° , 0.7° , 0.8° , 0.9° , and 1.0° . Biometric performance measures under the verification scenario are presented in Figure 16, with identification scenario presented in Figure 17.

There is an obvious linear trend in both verification and identification scenarios, as spatial accuracy is reduced, so is biometric accuracy. Further, as spatial accuracy reduction approaches 1.0° , the accuracy of both CEM-P and CEM-B biometric techniques becomes essentially random. This indicates that the spatial accuracy and stability of the eye tracking system is of paramount importance to the accuracy of biometric authentication. This also seems to imply that as the accuracy of eye tracking systems improves, so too will the accuracy of eye movement biometrics.

When interpreting these results, it is important to note that the dithering approach used to reduce spatial accuracy may not accurately model the spatial accuracy of specific individuals and systems. At this time, there exists no literature that mathematically describes the distribution of eye tracking error across the screen. As such, we have employed a uniform distribution of random noise, from which we hope to draw general conclusions.

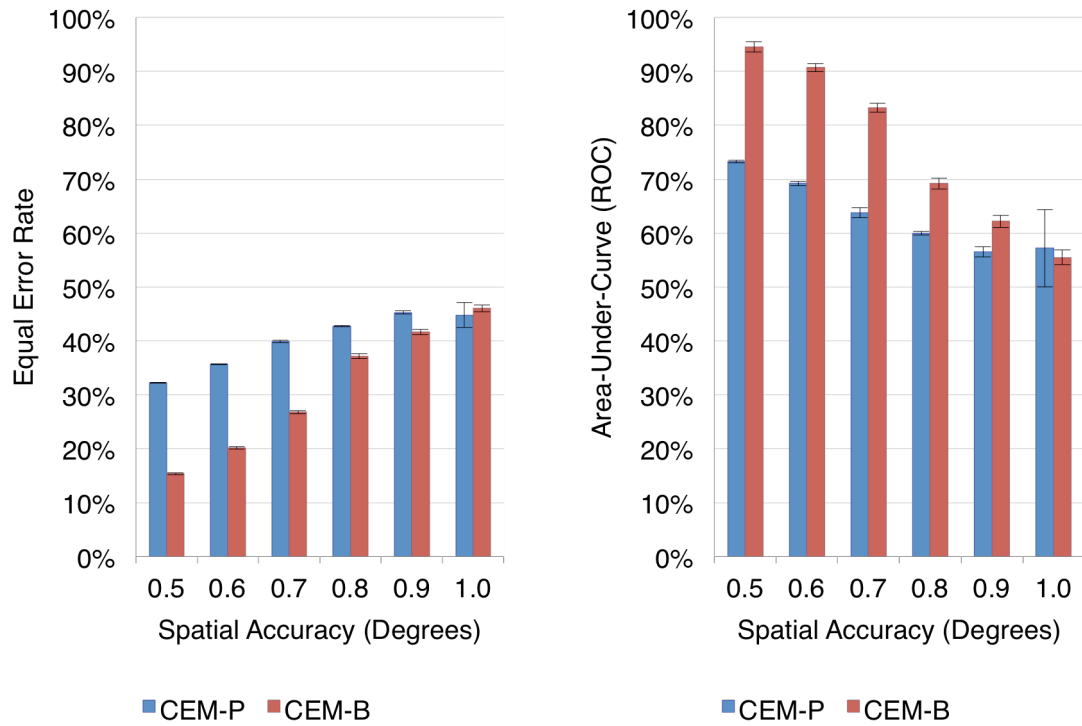


Figure 16. Spatial Accuracy (Verification).

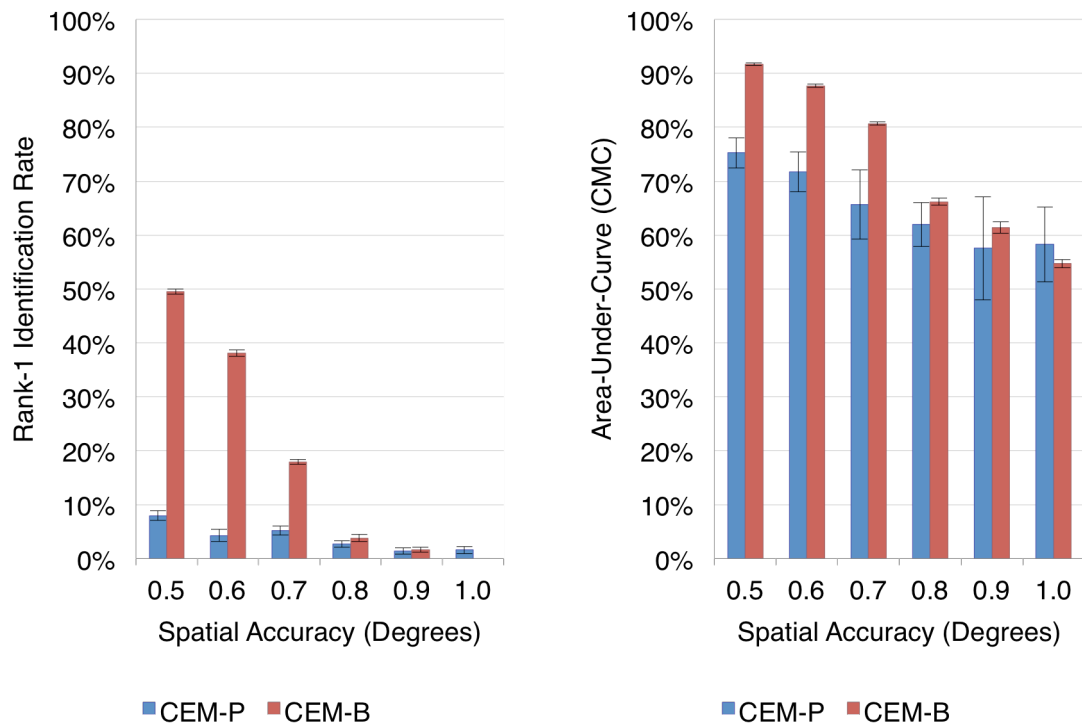


Figure 17. Spatial Accuracy (Identification).

The Effects of Age and Gender

To examine the impact of age on biometric accuracy, the recordings were split into two groups of approximately equal size, subjects 20 years of age and under, and subjects older than 20 years of age. The below-20 age group contained 151 subjects, while the above-20 age group contained 172 subjects. To examine the impact of gender on biometric accuracy, the recordings were split into two groups of approximately equal size based on gender. The male group contained 171 subjects, while the female group contained 152 subjects. Biometric performance measures under the verification scenario are presented in Figure 18, with identification scenario presented in Figure 19.

The Effects of Scaling

To examine the impact of scaling on the estimation of biometric accuracy, error rates were calculated on subsets of the total subject pool for the textual stimulus. Subsets of the subject pool were selected randomly according to a uniform distribution, without regard for factors such as age or gender; considered subject pools included: 50, 100, 150, 200, 250, 300, and 323 subjects. Biometric performance measures under the verification scenario are presented in Figure 20, with identification scenario presented in Figure 21.

Biometric accuracy was relatively consistent across the considered subject pools, though there was a slight reduction in rank-1 identification rates and a tendency towards tighter confidence interval bounds as subject pool increased. This seems to suggest that experiments conducted with as few as 50 subjects can achieve a reliable approximation of expected biometric accuracy for eye movement biometrics, though subject pools larger than 250 subjects are recommended.

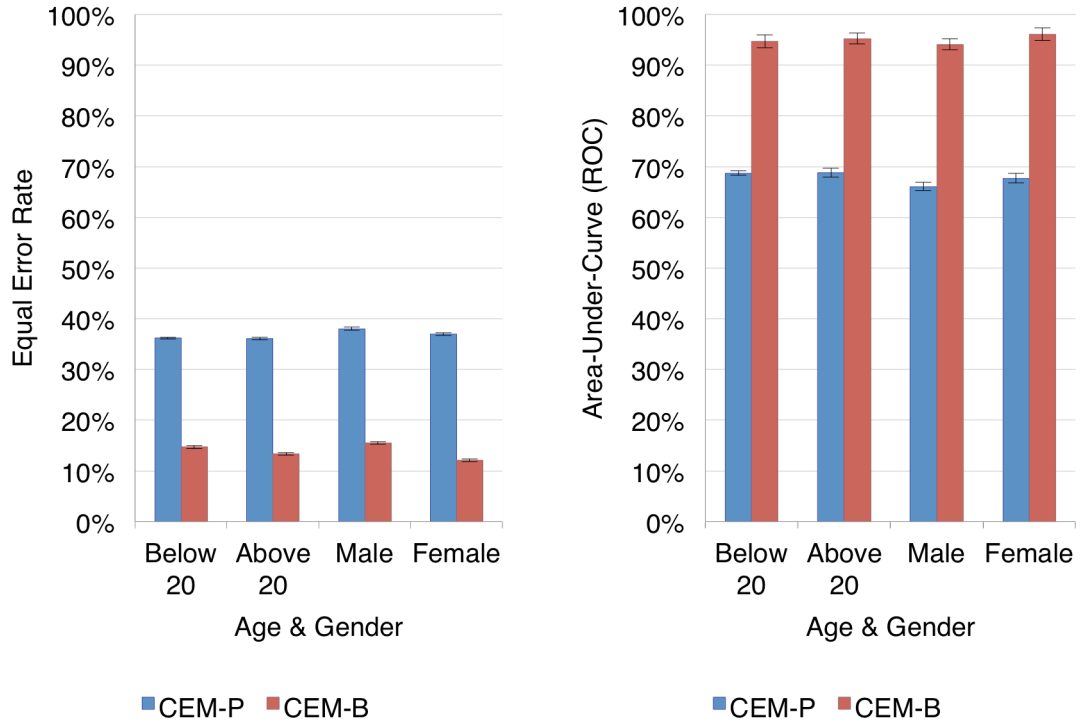


Figure 18. Age & Gender (Verification).

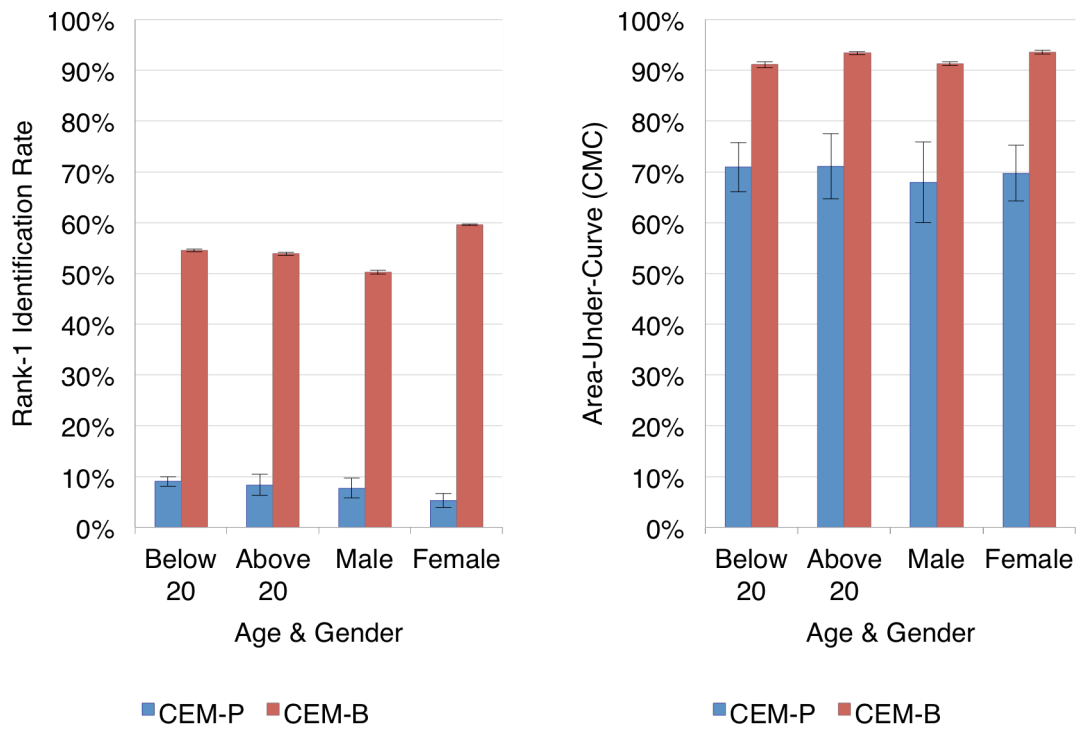


Figure 19. Age & Gender (Identification).

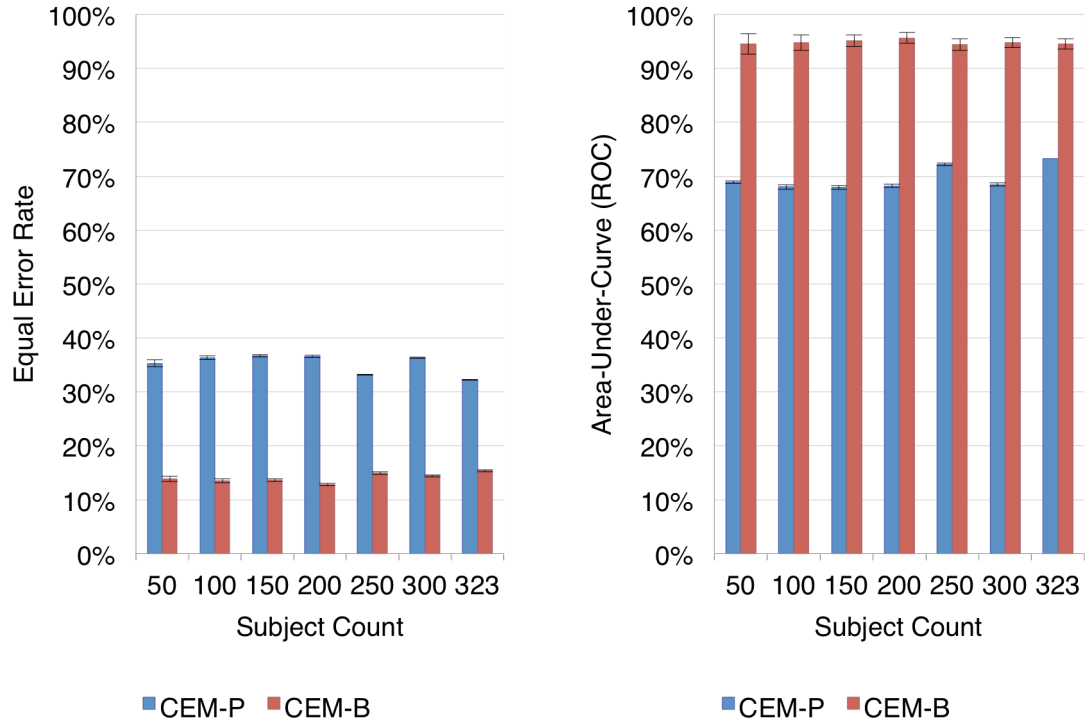


Figure 20. Scaling (Verification).

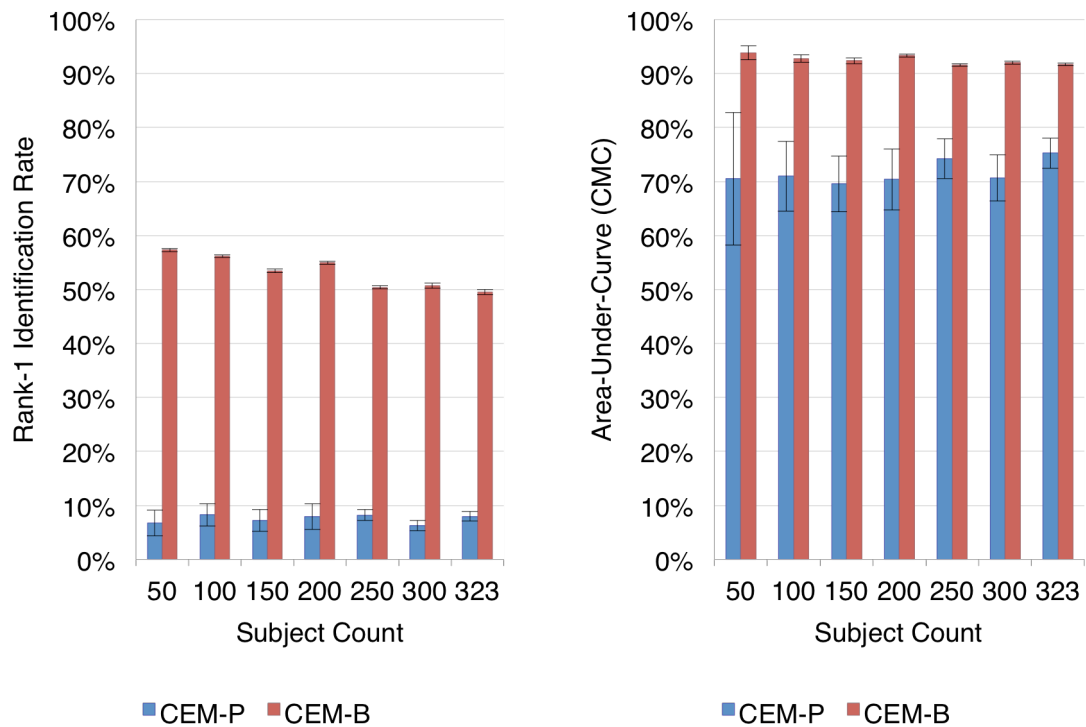


Figure 21. Scaling (Identification).

5. DISCUSSION

The results suggest the use of eye tracking equipment capable of at least 0.6° spatial accuracy and a minimum sampling rate of 75 Hz, though 0.5° spatial accuracy and 250 Hz sampling rate is recommended for best performance. While stimulus had little effect on the biometric viability of eye movements, the textual stimulus provided a slight advantage, potentially due to the unique properties of eye movements during reading. Further, there was little discernible difference in the biometric error rates produced for a subject pool of 50 individuals compared to a subject pool of 323 individuals.

Performance Analysis

In order to estimate the computational performance of the CEM-P and CEM-B techniques, the biometric framework was instrumented with profiling code to measure the execution times of specific modules and algorithms. Profiling was averaged over 100 iterations, using 4 parallel worker threads, for random subsets of 50 subjects with 2 recordings each (100 recordings total). The sensor module required an average 5.0 seconds (SD = 0.2) to load and parse all recordings; that is, 49.8 milliseconds per recording. The feature extraction module required 14.6 seconds (SD = 0.4) to classify and merge fixations and saccades across all recordings; or, 145.6 milliseconds per recording. The matching module required 96.0 seconds (SD = 3.4) to perform comparison, information fusion, and calculate match scores for the CEM-P technique, and 347.4 seconds (SD = 9.6) for the CEM-B technique for all recording combinations (100 choose 2 = 4950); or, 19.4 milliseconds per comparison for the CEM-P technique and 70.2 milliseconds per comparison for the CEM-B technique.

If we separate the boilerplate code and measure only the execution times of specific algorithms under the same circumstances, the CEM-P algorithm required an average of 58.2 seconds (SD = 1.3) to compare all recording combinations, while the linear combination of CEM-P match scores required 34.0 seconds (SD = 1.6) to combine match scores for all recording combinations; or, 11.8 milliseconds for comparison and 6.9 milliseconds for fusion of each comparison. The CEM-B algorithm required an average of 53.5 seconds (SD = 1.1) to compare all recording combinations, while the random forest required 282.0 seconds (SD = 4.9) to combine match scores for all recording combinations; or, 10.8 milliseconds for comparison and 57.0 milliseconds for fusion of each comparison.

Then, the total execution time for a single authentication attempt from sensor to decision is only 264.6 milliseconds for CEM-P and 315.4 milliseconds for CEM-B in a verification scenario, or more generally $49.8 * (N + 1) + 145.6 + 19.4 * N$ milliseconds for CEM-P and $49.8 * (N + 1) + 145.6 + 70.2 * N$ milliseconds for CEM-B in an identification scenario, where N is the total number of recordings in the database. According to standard usability practices [76], a delay of less than 100 milliseconds is typically regarded as unnoticeable, and a delay of less than 1 second is necessary to avoid interruption of the user thought process. Based on these criteria, both CEM-P and CEM-B can be considered suitable for real-time verification systems.

Liveness Detection

Liveness detection is an important problem in the biometric domain, due to the fact that it is relatively simple to create convincing replicas of many existing biometrics. For example, commercial iris identification systems can be spoofed by high-resolution

images of the eye printed on paper, with a hole to present the intruder's pupil, bypassing liveness detection mechanisms [20, 77]. There are further examples of fingerprint scanners being spoofed by common household items like gelatin [78], and face detection systems spoofed by printed images of the face [79-81].

The potential attack vectors for eye movement biometrics are limited, and may consist of mechanical or graphical representations. For a mechanical representation, the impostor must construct a robotic and anatomically convincing model of the human eye, and for a graphical representation, the impostor may utilize a graphics-generated model of the human eye presented on a display medium, such as a phone. Assuming that both representations of an artificial eye can be calibrated by the eye tracking system and bypass existing liveness detection techniques based on image analysis, the attack vector must generate an artificial eye movement signal that corresponds with the physical and neurological state of the intended target.

In 2013, Komogortsev and Karpov [26] generated a number of such attack vectors based on existing mathematical models of the human visual system. Using the maximum eigenvalues of feature vectors from the OPC technique, they were able to correctly classify 80-93% of recordings as human or spoof, over a subject pool of 32 participants. A similar study conducted with the CEM-P technique was able to achieve 100% classification accuracy on the same subject pool, using support vector machines to classify biometric feature vectors as human or spoof. Due to the non-paired, multi-dimensional feature vectors produced by the CEM-B technique, it is unsuited for either of these liveness detection techniques; but it is likely that future research will identify similar methods which demonstrate a high level of liveness detection capability.

Multi-Modal Biometrics

Multi-modal biometrics refers to the combination of multiple sources of biometric information to improve the overall system. While eye movements are not yet capable of competing with existing biometric standards in standalone systems, they possess a number of qualities that make them well suited for multi-modal systems. Most importantly, eye movements can be captured in tandem with image acquisition for face, iris, and periocular biometrics from a single image sensor [27]; this means that it is both cheap and efficient to implement multi-modal biometric systems that incorporate these traits, and further that many existing systems could be retrofitted to utilize these traits.

As well, many eye movement biometrics target different aspects of the human visual system, and can therefore be combined to improve the overall accuracy. For example, in 2012, Komogortsev et al. showed that a combination of CEM-P and OPC techniques increased authentication accuracy by 30% when compared to individual techniques [82], and that a multi-modal system utilizing both iris and eye movement biometrics improved authentication accuracy by 19% when compared to iris alone [83].

6. CONCLUSION

As technology advances, biometric traits are becoming easier to reproduce, circumventing the purposes of existing biometric identification techniques and leaving gaps in the efficacy of the systems that use them. Eye movements present a novel and unique solution to the challenges faced by modern biometrics. Consisting of both physical and neurological components, and due to the minute scale, the accurate replication of eye movements outside of a living subject is practically infeasible (if not impossible), providing an inherent level of liveness detection and counterfeit-resistance. Further, recent advances in video-oculography allow for the efficient capture of eye movements from even low-quality image sensors, reducing the cost of entry and enabling integration with many existing iris, periocular, and facial recognition systems.

This thesis has described the development of biometric techniques for the automated identification of human subjects based on patterns of eye movements that occur naturally during directed viewing of a visual stimulus. The proposed techniques were evaluated according to standard practices in the biometric field to assess performance under varying environmental conditions. The results suggest that reasonable biometric accuracy can be achieved with eye tracking equipment capable of capturing eye movements with at least 0.6° spatial accuracy and 75 Hz sampling rate, well within the capabilities of today's consumer-grade devices.

Limitations

The described techniques are obviously limited in their practical applications due to the relatively high error rates, an order of magnitude behind accepted physical biometrics such as fingerprint [3] and iris [19]; however, the research presented in this

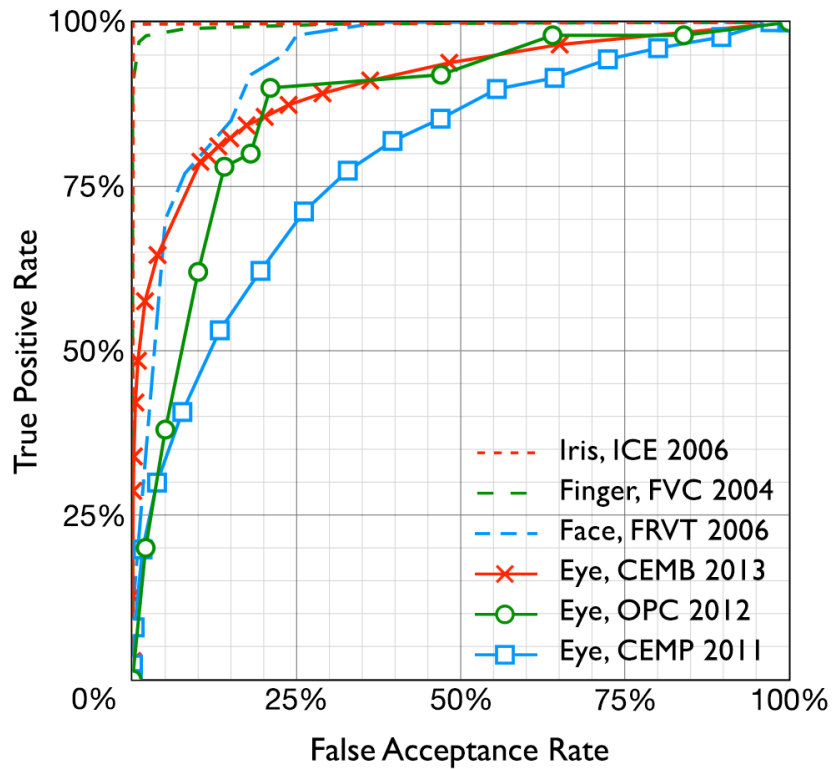


Figure 22. Growth of Eye Movement Biometrics.

thesis has demonstrated a direct increase in the biometric viability of eye movements to levels approaching modern face recognition [10, 11], illustrated in Figure 22. It is likely that more advanced techniques will be developed that may bring eye movements closer to current standalone systems, but even in their current state eye movement biometrics are ideal for inclusion in multi-biometric systems, and have been shown to improve both accuracy [83] and counterfeit-resistance [26].

It is worth noting that the relatively smaller number of acceptance comparisons to rejection comparisons results in false rejection rates that are statistically less sound than false acceptance rates. This is a common issue in biometrics, however, which results from the constraints on same-subject experimentation. To achieve equivalent amounts of acceptance and rejection comparisons, it would be necessary for each participant to

perform a number of trials greater than the total number of participants, which becomes increasingly prohibitive as the number of participants increases.

As well, it is likely that the dithering approach applied to reduce spatial accuracy may not accurately model the spatial accuracy of specific individuals and systems. There exists no current literature that mathematically describes the distribution of eye tracking accuracy across the screen. As such, a uniform distribution of random noise was used as an approximation, which may accurately model random system noise, but cannot account for variability in eye tracking accuracy caused by physiological or algorithmic sources.

Future Research

While there is an obvious need for algorithmic improvements to close the accuracy gap between eye movement biometrics and accepted biometric standards, such as fingerprints and iris, this is not the only avenue for continued study. As a relatively recent sub-field of biometrics, there are many aspects of eye movement biometrics which are yet unstudied. For example, while we have demonstrated that reduction in spatial accuracy and sampling rate may have a negative effect on biometric accuracy, there are known techniques that can be used to improve sample quality, and by extension biometric accuracy. Spatial accuracy can be improved by filtering techniques, such as the median filter or Kalman filter, and sampling rate can be improved by upsampling, utilizing polynomial or cubic spline interpolation. It will be necessary for future works to examine these techniques in detail to determine their ability to improve biometric accuracy.

In addition, there are various external factors that have not yet been examined. Studies have shown that altered mental state due to fatigue, caffeine, tobacco, or alcohol can cause variation in eye movements [25]; however, these effects have yet to be studied

in a biometric context, and further research will be necessary to quantify the extent of their influence. Further, the development of quality metrics, with which to identify and reject unsuitable eye movement recordings is still necessary to ensure that enrollment and authentication are not skewed by system noise.

Finally, ongoing advancements in hardware design and video-oculography techniques may lend future devices an incidental increase in biometric accuracy.

Increases in the frame rate and resolution of consumer-grade cameras will directly affect the spatial accuracy and sampling rate of video-oculography systems, as will algorithmic improvements in video-oculography techniques. Since face and iris detection are already key components in many video-oculography techniques, it is likely that future research will find interesting prospects in the design of multi-modal systems that are able to incorporate face, iris, and eye movement biometrics through a single image sensor.

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