Biometric Identification via an Oculomotor Plant Mathematical Model

Oleg V. Komogortsev[1], Sampath Jayarathna[1], Cecilia R. Aragon[2], Mechehoul Mahmoud[1]
[1]Department of Computer Science, Texas State University-San Marcos {ok11, sampath, mm2026@txstate.edu}
[2]Computational Research Division, Lawrence Berkeley National Laboratory, CRAragon@lbl.gov

Abstract

There has been increased interest in reliable, non-intrusive methods of biometric identification due to the growing emphasis on security and increasing prevalence of identity theft. This paper presents a new biometric approach that involves an estimation of the unique oculomotor plant (OP) or eye globe muscle parameters from an eye movement trace. These parameters model individual properties of the human eye, including neuronal control signal, series elasticity, length tension, force velocity, and active tension. These properties can be estimated for each extraocular muscle, and have been shown to differ between individuals. We describe the algorithms used in our approach and the results of an experiment with 41 human subjects tracking a jumping dot on a screen. Our results show improvement over existing eye movement biometric identification methods. The technique of using Oculomotor Plant Mathematical Model (OPMM) parameters to model the individual eye provides a number of advantages for biometric identification: it includes both behavioral and physiological human attributes, is difficult to counterfeit, non-intrusive, and could easily be incorporated into existing biometric systems to provide an extra layer of security.

CR Categories: I.6.4 [Simulation and Modeling]: Model Validation and Analysis; J.7 [Computers in Other Systems]: Process control, Real time.

Keywords: biometrics, oculomotor plant, eye tracking.

1 Introduction

Accurate, non-intrusive, and unforgeable identity recognition is an area of increasing concern to just about everyone in today's networked world, with the need for security set against the goals of easy access. The majority of the world's population would like secure access to their assets without risk of identity theft, yet do not want to be subjected to inconvenient or intrusive detection systems. Many of the most-commonly utilized methods for identity determination have known problems. For example, password verification has demonstrated many weaknesses in areas of accuracy (there is no way to verify that the individual typing the password is actually its owner, unless a temporal pattern recognition system is employed [Joyce and Gupta 1990]), usability (people forget passwords [Wiedenbecka et al.]), and security (people write them down or create easy-to-hack passwords [Schneier 2005]) .

As a result, techniques of biometric identification, defined as methods for identifying persons based on uniquely identifying physical or behavioral traits, have been garnering significant recent interest [Daugman 2002; Jain et al. 1999; Kasprowski 2004]. The potential for advancement in biometric identification methods is substantial due to recent improvements in computer processing power, database size, and sensor technologies.

There are a number of methods employed today for biometric purposes. Some examples include the use of fingerprints, iris and retina scans, face recognition, hand/finger geometry, voice recognition and eye movements [Bednarik et al. 2005; Daugman 2002; Jain et al. 1999; Josephson and Holmes 2002; Kasprowski 2004] .

Current biometric identification technologies are somewhat fraud resistant, but they are not completely foolproof and may be compromised with available technologies. Even though fingerprint identification is a popular methodology, such systems have been demonstrated to be insufficiently invulnerable in high security environments. Several recent studies have shown that it is possible to fool fingerprinting systems with common household articles such as gelatin [Williams 2002].

Face recognition systems are still undergoing research to improve their precision and recall [Jain et al. 1999; Zhao et al. 2003]. Additionally, identical twins (1:10,000 probability), and related issues such as family resemblance may bring the reliability of such systems into question. It is also possible to use still images and video footage of a person to bypass a face recognition system.

Further disadvantages of many of these methods involve the ability to forge replicas – in some cases even causing injury to the owner of the body part used for biometric identification. Eye movements, in contrast, constitute a behavioral characteristic which is extremely difficult to forge, and which cannot be stolen from an individual.

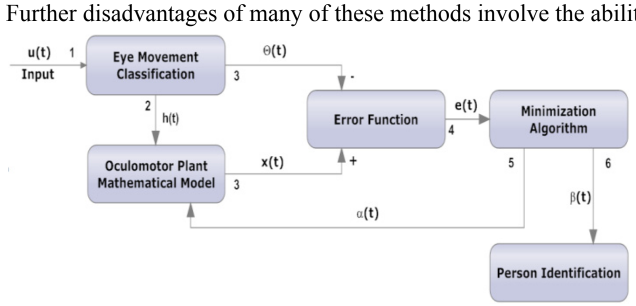

Figure 1. Biometric Identification Model.

The challenge lies in classifying eye movements in such a manner that the differences between individuals are more significant than changes in a single human's behavior over time. In order to do this, we turn to physical and behavioral characteristics that are relatively constant in an individual human over their lifetime: the physical structure and behavior of the muscles that move the eye. We propose a person identification method based on the Oculomotor Plant Mathematical Model (OPMM) developed by [Komogortsev and Khan 2008]), derived from earlier work by Bahill [Bahill 1980]. The OPMM models a human eye as a system that consists of an eye globe driven by a set of extraocular muscles. This system models the anatomical structure of the human eye, where each extraocular muscle is driven by a uniquely defined

ETRA 2010, Austin, TX, March 22 – 24, 2010.
© 2010 ACM 978-1-60558-994-7/10/0003 $10.00

neuronal control signal and consists of series elasticity, length tension, force velocity, and active tension components. However, the specific values for the previously determined OPMM parameters were obtained from studies that examined a single individual. In this paper, we analyze eye movement traces and derive a unique vector of values corresponding to each person over a sample set of 41 individuals. We report our results and discuss the challenges and advantages provided by biometric identification via an OPMM.

2 Biometric Identification by Oculomotor Plant Mathematical Model

An overview of our method for biometric identification is depicted in Figure 1. The recorded eye movement signal u(t) from a single individual is supplied to the "Eye Movement Classification" module that classifies eye position signal into fixations and saccades. We focus on the detected saccade trajectories, represented by Θ(t) in the diagram. The detected saccade parameters, the onset and offset coordinates and amplitudes of the detected saccades, depicted by h(t), are sent to the second module labeled OPMM, which generates simulated saccade trajectories represented by the signal x(t). The difference between detected saccade trajectories Θ(t) and simulated saccade trajectories x(t) is computed by the "Error Function" module and the resulting error e(t) is produced. The e(t) signal serves as an input to the "Optimization Algorithm" module that provides feedback to the OPMM module with the goal of minimizing the error e(t). After several iterations, the optimum OPMM parameters in the form of an "Oculomotor Coefficients Vector" module are supplied to the "Person Identification" module which performs the actual identification. Detailed descriptions of each module are provided in the sections to follow.

3 Eye Movement Classification

We employed the Velocity-Threshold (I-VT) algorithm [Salvucci and Goldberg 2000] with threshold of 55°/s in the Eye Movement Classification module to split an eye movement recording into fixations and saccades. The original I-VT algorithm was modified to output such characteristics of an individual saccade as onset (θ_{x_onset}), offset (θ_{x_offset}) coordinates, amplitude (θ_{sac_amp}) and the coordinates of all eye position points between the onset and the offset. The outputs of this module are the detected saccade trajectories Θ(t) and the onset and offset coordinates and the amplitude of the detected saccades, h(t). Θ(t) is passed as input to the Error Function module described in Section 5, and h(t) is used as input to the OPMM module described in the following section.

4 Oculomotor Plant Mathematical Model

Six extraocular muscles rotate the eye globe in its socket. The muscles are innervated by a neuronal control signal generated by the brain. During saccades this signal is a pulse step, where pulse characteristics are encoded by the velocity command and step characteristics are encoded by the positional command [Leigh and Zee 2006]. The horizontal OPMM described in [Komogortsev and Khan 2008] models all of the described properties of the Oculomotor Plant as linear springs or damping components, providing approximate values for the parameters describing these components.

5 Error Function

Saccade trajectories generated by the Eye Movement Classification module and the OPMM module are supplied to the Error Function module, where the error e(t) in a form of the Root Mean Squared Error (RMSE) is computed between the detected x(t) and the simulated by the OPMM $\Delta\theta(t)$ eye position signal.

When multiple saccades are detected for an individual by the eye movement classification algorithm, the average of the RMSEs from the detected and simulated trajectories is presented as a final e(t). Note that a good approximate solution of the OPMM equations creates an eye movement trajectory with a sampling rate of 1000Hz [Komogortsev and Khan 2008]; in the case where the eye tracking frequency is lower, the signal $\Delta\theta(t)$ is down-sampled to match the eye tracking frequency.

6 Optimization Algorithm

6.1 Oculomotor Plant Parameters Vector

The goal of the Optimization Algorithm module is to provide a set of better values for the OPMM parameters by minimizing error e(t). The OPMM's parameters, such as passive elasticity, viscosity, series elasticity, length tension, force velocity relationship, height and width on the neuronal control signal, are unique for each individual. Some of these parameter values were previously estimated from a record of just one subject [Bahill 1980]. Moreover, some of the parameters such as length tension and series elasticity were derived by manual data fitting and hand-drawn straight line approximations [Bahill 1980]. The values of the OPMM parameters derived in this way can be improved to provide a much better fit for a specific individual.

One way to derive more accurate values for the OPMM parameters is to employ an optimization algorithm that selects new values for the parameters with an objective of minimizing the error e(t). It is important to note that some parameters provide higher impact than others on the simulated eye movement trajectory [Bahill 1980]. The ranking of the parameters starting with those providing the highest influence on the simulated saccade trajectory is as follows: the width of the pulse of the neuronal control signal for the agonist muscle (LR_p), pulse height of the neuronal control signal for the agonist muscle (LR_s), length tension (K_{LT}), series elasticity (K_{SE}), passive viscosity of the eye globe (B_p) and force velocity relationship in the agonist muscle represented by the damping component (B_{AG}), combined passive elasticity of the eye globe and all extraocular muscles (K_p), eye globe inertia (J). All these parameters are selected for actual person identification.

6.2 Optimization Algorithms & Strategies

<u>**Optimization Algorithms:**</u> We employed two optimization algorithms to determine optimized values for the OPMM parameter vectors (LR_p, LR_s, K_{LT}, K_{SE}, B_{AG}, K_p, J) with an objective of minimizing the error e(t).

First, the Trust-Region (TR) algorithm that uses the interior-reflective Newton method was applied [Coleman and Li 1996]. The TR algorithm is an optimization method that searches for a better value in an area called the trusted region around the initial parameter value. At the start, the region of search is close to the initial parameter value and if a better value is found the trusted region size is increased, otherwise the size of the search region is reduced.

Additionally, the Nelder-Mead (NM) simplex algorithm was applied [Lagarias et al. 1998]. This algorithm employs a simplex of n+1 points for a vector y with n dimensions. At the beginning the algorithm builds a simplex around the initial value i by adding a percentage value of each component of the vector y. Resulting values are employed as elements of the simplex in addition to initial value i. As a result new points of the simplex are generated until the simplex diameter reaches a specified threshold.

Optimization Strategies: Two strategies are employed to optimize OPMM parameters with the TR and NM algorithms.

Strategy 1: the OPMM parameters are optimized sequentially. An already optimized parameter remains in the parameter vector. The subsequent parameters are optimized based on the newly optimized value of the previous parameter. For example, the value of the K_{lt} (after optimization) is employed for subsequent optimization of K_{se}, and the values of both K_{lt}, K_{se} (after optimization) are employed for subsequent optimization B_p, etc.

Strategy 2: the OPMM parameters are optimized sequentially. An already optimized parameter is saved in the temporal parameter vector and the value of this parameter in the original vector is restored to the original value. The subsequent parameters are optimized based on the original values of the remaining parameters. For example, the value of the K_{lt} (after optimization) is stored in a temporal vector and the estimation of the K_{se} occurs with the initial value of the K_{lt}. The K_{se} is stored in the temporal vector. The optimization of the B_p is based on the initial values of K_{lt}, K_{se}, etc. When all OPMM parameters are estimated the temporal vector holds the data for person identification.

7 Person Identification

The input to the Person Identification module consists of a set of OPMM parameter vectors estimated for each qualifying saccade. The output is an authorization score classifying each saccade as belonging to an authorized user or an imposter. In order to perform the classification, we evaluated two different statistical algorithms, the K-nearest neighbor (KNN) algorithm, and C4.5. KNN is a very simple instance-based learning algorithm, and C4.5 is a freely-available classifier that builds a decision tree based on the concept of information entropy [Shakhnarovich et al. 2005]. The eye movement record for an individual consists of multiple saccades, and as a result the biometric identification record for each individual will consist of a set of OPMM parameter vectors. We work with the complete set of per-saccade parameter vectors, and split them into a training and a testing set to perform identification.

The following methodology is used to partition each participant's data into training and testing sets. Each participant data set containing exactly two records is arbitrarily declared to be an imposter, and included only with the testing set. For each participant data set containing three records or more, the parameter vectors are inserted into both testing and training sets as authorized users; the first record is inserted into the testing set and subsequent samples are inserted into the training set. We decided to split the sets in this way because of the relatively small amount of test data; however, it is possible that we have thereby introduced a systematic bias into the training set, and we plan further experiments to eliminate this possibility. We also note that samples identified as imposters, although not included in the training set, are still tracked in order to obtain the correct false acceptance rate (FAR) value for available imposters.

KNN Classification Algorithm: The *k-nearest neighbor* (KNN) algorithm [Shakhnarovich et al. 2005] (in our implementation, k=5) is one of the simplest classification algorithms, but is accurate and powerful when samples with similar classification tend to appear nearby. 'Nearby' means that the distance between similar classifications is generally closer than the distance between samples with different classification [Kasprowski 2004]. For each oculomotor parameter coefficient, a distance value is obtained and recorded into a distance vector. The pseudocode for the algorithm can be found in [Komogortsev et al. 2009].

C4.5 Classification Algorithm: C4.5 is a classification algorithm which builds a decision tree from a training set of data, where the split at each node maximizes the information gain which represents the difference in entropy in the set after and before the split. We selected a decision tree classifier because they are robust to noisy data and C4.5 because it is widely used and easy to implement. The pseudocode for the algorithm can be found in [Komogortsev et al. 2009].

7.1 Methodology

Apparatus: The experiments were conducted with a Tobii x120 eye tracker [Tobii 2009], 24-inch flat panel screen with resolution of 1980x1200 pix. Subjects were seated approximately 710 mm from the eye tracker. Sampling of eye position coordinates was done at 120Hz.

Accuracy test: An accuracy test was employed prior to the experiment providing us with average calibration error and invalid data percentage for each subject. The accuracy test is described in more detail in [Koh et al. 2009].

Eye Movement Invocation Task: The stimulus was presented as a 'jumping point' with vertical coordinate fixed to the middle of the screen. The first point was presented at the middle of the screen; the subsequent points moved horizontally to the left and to the right of the center of the screen with a spatial amplitude of 20°, providing average stimuli amplitude of approximately 19.3°. The jumping sequence consisted of 15 points including the original point in the center, yielding 14 saccades for each participant. After each jump, the point remained stationary for 1.5s before the next jump was initiated. The size of the point was approximately 1° of the visual angle with the center marked as a black dot. Each point consisted of white pixels (except for the central black dot), with the remainder of the screen left black.

Participants: The test data consisted of 68 student volunteers ages 18-25 with an average age of 21.2 and standard deviation of 3.2, 24 males and 44 females, with normal or corrected-to-normal vision. None of the participants had prior experience with eye tracking. The data collection was verified to be accurate by employing two parameters, the average calibration error of the right eye and the invalid data percentage of the right eye. The data analyzer was instructed to discard recordings from subjects with a calibration error of $> 3.0^{\circ}$, with mean of 1.25°, standard deviation of 0.77° and invalid data percentage of >50%. Only 41 subject records passed these criteria, resulting in mean accuracy of 1.25º (SD=0.77°) and a mean invalid data percentage of 12.43% (SD=17.22%). Only saccades with amplitudes of 17-22º were employed for biometric identification.

Performance evaluation metrics: Performance evaluation of a biometric system is measured with the following two parameters.

False Acceptance Rate ***(FAR)*** – The ratio of the number of imposter samples classified as authentic to the total number of all the imposter samples. This metric measures the probability that the system incorrectly matches the input pattern of the testing set to a non-matching template in the training set. It measures the percent of invalid inputs which are incorrectly accepted. *False Rejection Rate* ***(FRR)*** – The ratio of the number of authentic samples classified as imposters to the number of all the authentic samples. This metric calculates the probability that the system fails to detect a match between the input pattern of the testing set and a matching template in the training set. It measures the percent of valid inputs which are incorrectly rejected.

8 Results

We conducted the classification with both the KNN and C4.5 algorithms on each of the OPMM parameters, and determined that the best results were obtained with KNN utilizing the TR algorithm with optimization strategy 1 for the length tension coefficient. These results improve on previous work in the field by Kasprowski [Kasprowski 2004] and Bednarik et al [Bednarik et al. 2005]. C4.5 did not produce acceptable results with the tested algorithm parameters.

KNN: The smallest FAR and FRR values were achieved with the Trust-Region algorithm using optimization strategy 1 for the length tension coefficient (K_{LT}). The two next best results were provided by the Nelder-Mead algorithm using optimization strategy 1 for the passive elasticity coefficient (K_p) and the distance created by all parameters (D). The FAR=5.4% and FRR=56.6% results improve on the previously reported results of FAR=9.4% and FRR=63.4% given by Kasprowski in 2004 using the KNN algorithm [Kasprowski 2004].

C4.5: Unfortunately, we did not obtain good FAR rates with the C4.5 algorithm, even if we accepted an increase in FRR. We believe the FAR can be improved by further tuning of the algorithm parameters. The best FAR=80% and FRR=0% values were achieved by Nelder-Mead with optimization strategy 2. For comparison, Kasprowski obtained an FAR of 45.8% and an FRR of 12.4% using C4.5 in 2004 [Kasprowski 2004].

9 Discussion, Conclusions and Further Work

We have introduced a novel method of biometric identification based on the utilization of Oculomotor Plant Mathematical Model parameters from horizontal positive saccadic eye movements. We evaluated the effectiveness of this method via two different statistical classification techniques on a data set of horizontal saccadic eye trajectories collected from 41 human participants, and achieved promising results using the k-nearest neighbor classification algorithm. Our results improve on previous biometric methods involving eye movements.

The OPMM method of biometric identification leverages physiological and behavioral characteristics that are unique to each individual – the mechanical properties of the eye globe and its musculature – rather than simply looking at unprocessed saccadic trajectories. The resulting additional information provides further structure to the eye movement data and perhaps this is what leads to the improved performance of our method over previous work. A further advantage of the proposed method is its use of a dynamic oculomotor plant model consisting of the eye globe and extraocular muscles that is extremely difficult to counterfeit.

Via our tests, we demonstrated the potential to distinguish authorized users from imposters with this technique. However, further testing with larger subject pools and different statistical classification algorithms is needed to improve on the accuracy rates of our method. Nevertheless, this technique shows promise for improving the state of biometric identification. This new method could also be easily combined with existing biometric identification systems that incorporate digital cameras to scan the face or iris, to provide an additional layer of security. In an ever-more security-conscious and highly networked world, non-intrusive and unforgeable personal identity-based authorization methods will become increasingly critical across a wide range of commercial and government applications.

10 References

BAHILL, A. T., 1980. Development, validation and sensitivity analyses of human eye movement models, *CRC Critical Reviews in Bioengineering* 4, 311-355.

BEDNARIK, R., KINNUNEN, T., MIHAILA, A., AND FRÄNTI, P., 2005. *Eye-Movements as a Biometric*.

COLEMAN, T. F., AND LI, Y., 1996. An interior trust region approach for nonlinear minimization subject to bounds, *SIAM Journal on Optimization* 6, pp. 418–445.

DAUGMAN, J., 2002. How iris recognition works, *Image Processing. 2002. Proceedings. 2002 International Conference* 1, I-33- I-36.

JAIN, A., HONG, L., AND KULKARNI, Y., 1999. A Multimodal Biometric System Using Fingerprint, Face, and Speech, *In International Conference on AVBPA*, 182-187.

JOSEPHSON, S., AND HOLMES, M. E., 2002. Visual attention to repeated internet images: testing the scanpath theory on the world wide web, *In ETRA 02: Proceedings of the 2002 symposium on Eye tracking research & applications*, 43-49.

JOYCE, R., AND GUPTA, G., 1990. Identity authentication based on keystroke latencies, *ACM Communications* 33, 168--176.

KASPROWSKI, P., 2004. *Human identification using eye movements*(Silesian University of Technology, Gliwice).

KOH, D. H., GOWDA, S. A. M., AND KOMOGORTSEV, O. V., 2009. Input evaluation of an eye-gaze-guided interface: kalman filter vs. velocity threshold eye movement identification, *Proceedings of the 1st ACM SIGCHI symposium on Engineering interactive computing systems*, 197-202.

KOMOGORTSEV, O., V., AND KHAN, J., 2008. Eye Movement Prediction by Kalman Filter with Integrated Linear Horizontal Oculomotor Plant Mechanical Model, *ETRA Symposium 2008*, 229-236.

KOMOGORTSEV, O. V., JAYARATHNA, U. K. S., ARAGON, C. R., AND MECHEHOUL, M., 2009. *Biometric Identification via an Oculomotor Plant Mathematical Model*. http://ecommons.txstate.edu/cscitrep/16/.

LAGARIAS, J. C., REEDS, J. A., WRIGHT, M. H., AND WRIGHT, P. E., 1998. Convergence Properties of the Nelder--Mead Simplex Method in Low Dimensions, *SIAM J. on Optimization* 9, 112-147.

LEIGH, R. J., AND ZEE, D. S., 2006. *The Neurology of Eye Movements*(Oxford University Press).

SALVUCCI, D. D., AND GOLDBERG, J. H., 2000. Identifying fixations and saccades in eye tracking protocols, *ETRA Symposium*, 71-78.

SCHNEIER, B., 2005. Two-factor authentication: too little, too late, *ACM Communications* 48, 136.

SHAKHNAROVICH, G., DARRELL, T., AND INDYK, P., 2005. *Nearest-Neighbor Methods in Learning and Vision*(MIT Press).

TOBII, 2009. http://www.tobii.com.

WIEDENBECKA, S., WATERS, J., BIRGET, J.-C., BRODSKIY, A., AND MEMON, N. PassPoints: Design and longitudinal evaluation of a graphical password system, *International Journal of Human-Computer Studies* 63, 102-127.

WILLIAMS, J. M., 2002. Biometrics or ... biohazards?, *Proceedings of the 2002 workshop on New security paradigms*, 97-107.

ZHAO, W., CHELLAPPA, R., AND PHILLIPS, P. J., 2003. Face recognition: A literature survey, *ACM Computing Surveys (CSUR)* 35, 399-458.