A Multiview Facial Analysis Technique for Identity Authentication

Biometric systems, which use people's physiological characteristics for identification or authentication, have become increasingly popular for countering fraud. In this article, we describe a face recognition system that uses a new distance measure for authentication. It performs matching on a fusion of multiple views of each person.

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In Mark Weiser's seminal article on ubiquitous computing, he described a world in which computers work harmoniously and transparently with human users, serving human users in different aspects of their lives.¹ Although some of his ideas seemed far-fetched at the time, many of the enabling technologies necessary for realizing Weiser's vision are now becoming avail-

able. For example, technological advancements in hardware mean that physical computing machines (such as personal computers) will gradually become invisible to human users because both mobile clients and infrastructure systems can work seamlessly and unob-

trusively.² You can already disguise mobile client devices by embedding them into personal belongings that people carry or wear—handbags, shoes, cellular phones, and so on. Similarly, software technology developments ensure the ready integration and interoperation of diverse systems.³

However, many questions remain on how to effectively integrate these components—the building blocks of pervasive computing.⁴ In this article, we focus on using biometric-based authentication techniques to address privacy and trust issues.

Biometrics for ubiquitous computing environments

Traditional person recognition methods do not meet today's needs. Large sums of money have changed hands based on a signature, identity cards, or passwords—all unreliable or forgeable sources. Additionally, you can lose (through theft or absent-mindedness) smart cards and similar devices (although you can reduce the risk by embedding them into things or eventually the human body⁵). So, the need increases for fast, accurate, and user-friendly automatic person recognition systems—ideally, ones that don't need human attention. Such systems could address purposes such as physical access control (border control and access to secure areas), traditional business transactions, and even the management of surrogate computing resources, online transactions, and criminal investigations.

In recent years, biometrics has gained importance as a research area.^{6,7} Biometrics relates to a person's physiological features (fingerprints, face) and behaviors (speech), which you can use to distinguish one person from another. In fact, law enforcement agencies have used fingerprinting technology in forensics for many years. A biometric system should be nonintrusive to users. For example, most users would deem face or speech recognition more acceptable than an iris scan.

Figure 1. Overview of our experimental system: (a) enrollment; (b) authentication (fused multiview analysis).

In our research, we focus on face recognition (see the related sidebar)—one of biometrics’ least intrusive forms—and aim to promote the goal of invisibility mentioned earlier. You can classify face recognition as *authentication* and *identification*. In authentication, we try to answer the question “is the person claiming to be person X really person X?” This gives a binary decision. In identification, we want to find the person most likely to be X from among a pool of candidates in a database.

Different performance metrics exist for authentication and identification.⁸ For identification, metrics focus on the likelihood that the correct answer appears in the list of top (say 10) matches; for verification, the primary performance measure is the tradeoff between false acceptance and false rejection rates, which leads to the consideration of an equal error rate line. Typically, we concentrate on plotting FRR against FAR to compare different systems’ or system parameters’ performance. This results in *receiver operating characteristic* curves. So, the line given by $FRR = FAR$ in a ROC plot is the EER.

In our research, we focus on authentication. You can use it to manage access control to surrogate computing resources during cyber-foraging activities. Most research concentrates on frontal facial analysis.^{9,10} To improve system robustness, others have developed multimodal approaches that fuse together different biometrics.¹¹ However, we believe optimizing a single-modal system minimizes deployment costs and could benefit any multimodal system.

You can improve a face recognition system’s robustness by taking multiple views of a person’s face at different angles using essentially the same equipment as frontal-only analysis. We developed a multiview face recognizer for authentication that meets these design objectives:

- *Robust against variations.* Operates under different conditions and applies to a high percentage of the population.
- *Cost effective.* Incurs minimal deployment costs.
- *Accurate and reliable.* Has excellent performance distinguishing between people and excellent EER performance.
- *User-friendly.* Is nonintrusive and fast.

As Figure 1 shows, we target our solution toward the authentication of users who are willing to have an enrollment process capture images of their faces. These captured images form a knowledge base used for subsequent authentication by comparing person X’s stored image with the image of a person claiming to be X.

Significance-based multiview Hausdorff distance

Suppose a set of feature vectors (nodes) N_A , or *model points*, represents an image A and another set N_B , or *test points*, represents image B. (See the “Face recognition” sidebar for more information.) Traditional methods that assign the same weight to all

points in N_A and N_B clearly lead to suboptimal results because different feature points contribute differently toward an overall face description. In this article, we apply a new variant of Hausdorff distance called the significance-based multiview Hausdorff distance (see the “Face Recognition” sidebar).

SMVHD differs from other HD variants in two ways. First, we apply the notion of significance associated with each point. Second, we fuse together multiple views of the same nonrigid object (the face) taken from different viewpoints. (Using multiview images for facial analysis is not entirely new. The TrueFace system (see www.biometricgroup.com/a_bio1/vendor/miros.html) uses two images. However, its reliance on neural network technology might account for a relatively long computational time—a claimed recognition time of 2 s.) More specifically, suppose

$$M^1 = \{m_1^1, m_2^1, \dots, m_{p_1}^1\},$$

$$M^2 = \{m_1^2, m_2^2, \dots, m_{p_2}^2\}, \dots,$$

Face Recognition

Eigenface, elastic graph matching, and backpropagation neural nets are traditionally considered the three major approaches developed for face recognition.^{1,2} Because a comprehensive survey judged EGM the best of the three techniques,² we won't discuss the other two techniques here. EGM entails the analysis of a face represented by a set of feature descriptors located at the nodes of a sparse grid (or lattice).^{3,4} Due to relatively simple processing, the nodes are typically distributed evenly over a rectangular grid. However, you can also situate the nodes at important feature points (for example, eyes) called fiducial points.

Figure A illustrates the basic idea of EGM (using a rectangular grid).² The grid's nodes form a set of feature vectors that mathematically describe the face's characteristics. Suppose we define a 2D image lattice S and within it a smaller, coarser lattice S_1 . The face template, which characterizes the face's features, is a vector field $\mathbf{c} = \{\mathbf{c}_i, i \in S_1\}$, where $\mathbf{c}_i$ is a feature vector at node i . During recognition, we require another vector field called the face vector field $\mathbf{x} = \{\mathbf{x}_j, j \in S\}$. So, $\mathbf{x}$ is defined over the original finer lattice S . You obtain the distance $d(\mathbf{c}, \mathbf{x})$ by finding a best match M between $\mathbf{c}$ and $\mathbf{x}$, where M is a mapping between S and S_1 . EGM aims to minimize an energy (or cost) function $E(M)$.

Comparing two faces (between person X 's stored image and a newly captured image of the person claiming to be person X) entails minimizing $E(M)$ in two steps. In step 1, as in conventional template matching without any defor-

mation, moving $\mathbf{c}$ around $\mathbf{x}$ performs rigid matching. Once we find the position with the minimum distance, we obtain an initial match M_0 with energy $E(M_0)$. In step 2, stretching S_1 performs deformable matching, to allow $\mathbf{c}$ to deform to further minimize the energy function. This flexibility provides robustness against changes in illumination and variations in nonrigid objects such as faces.

More recently, researchers have proposed other face recognition techniques such as linear discriminate analysis and support vector machines.⁵ In our research, we apply a technique called the dynamic two-strip algorithm (Dyn2S),⁶ which relies on detecting dominant points on the facial edges. This approach somewhat resembles EGM in that it extracts dominant points from a person's face to form a mathematical description of the face image instead of using a grid in a particular form.

Because we need to quantitatively analyze a match between two images, we must consider a suitable distance measure. For example, suppose a set of feature vectors (nodes) N_A , *model points*, represent an image A and another set N_B , *test points*, represents image B . Then, matching images A and B amounts to determining whether the dis-

Figure A. Illustration of elastic graph matching: (a) 2D image lattice S and within it a smaller, coarser lattice S_1 ; (b) placing S_1 on the face image.

$$M^n = \{m_1^n, m_2^n, \dots, m_{p_n}^n\}$$

are n point sets representing the features in object M 's n model views and

$$T^1 = \{t_1^1, t_2^1, \dots, t_{q_1}^1\},$$

$$T^2 = \{t_1^2, t_2^2, \dots, t_{q_2}^2\}, \dots,$$

$$T^n = \{t_1^n, t_2^n, \dots, t_{q_n}^n\}$$

are the corresponding n point sets repre-

senting the features in test object T 's n views from the same viewpoints as in the model M . In this formulation, $p_1, p_2, \dots, p_n$ and $q_1, q_2, \dots, q_n$ are the point numbers, which are used for indexing, in the model and test views. So, we must let only the i th point in the k th view point $t_i^k \in T^k$ match with the points in M^k , the k th view of M (see Figure 2).

We define the SMVHD between M and T as

$$H_{SMVHD}(M, T) = \max(h_{SMVHD}(M, T), h_{SMVHD}(T, M)).$$

In turn, we define the directed SMVHD from M to T and from T to M as

$$h_{SMVHD}(M, T) = \frac{1}{\sum_{k=1}^n \sum_{m_i^k \in M^k} \text{Sig}_{m_i^k t_j^k} \cdot \min_{t_j^k \in T^k} \|m_i^k - t_j^k\|}$$

tance between the respective nodes in N_A and N_B are sufficiently close. An authentication system makes a binary decision based on this proximity. So, an effective distance measure is critically important in determining a face recognizer's performance for authentication.

Hausdorff distance is a popular distance measure well suited to establishing similarity between two sets of points.⁷ Unlike most other methods that rely on a rigid point-to-point relationship between model and test points, you can determine HD without an explicit relationship. This makes HD particularly useful for comparing nonrigid objects. In fact, some commercial products—for example, BioID⁸—use HD for face location and eye location.

Mathematically, if we have two finite sets of feature points $M = \{m_1, m_2, \dots, m_k\}$ (representing a model) and $T = \{t_1, t_2, \dots, t_n\}$ (representing a test image), we can define HD as

$$H(M, T) = \max(h(M, T), h(T, M)), \quad (A)$$

where

$$h(M, T) = \max_{m_i \in M} \min_{t_j \in T} \|m_i - t_j\| \quad (B)$$

and $\|m_i - t_j\|$ denotes the Euclidean norm on points of M and T . The function $h(M, T)$ is the *directed* HD from M to T . It identifies the point $m_i \in M$ that is the farthest from any point of T and measures the distance from m_i to its nearest neighbor in T . The Hausdorff distance $H(M, T)$ is the maximum of $h(M, T)$ and $h(T, M)$. So, it measures the degree of mismatch between two sets by measuring the distance of point M that is farthest from any point of T and vice versa.

Unfortunately, this HD traditional definition is very sensitive to perturbations caused by even a few outlying points, which might result from imperfection in image segmentation. Researchers found that a modified HD is less susceptible to outlying points.⁹ In fact, Equation C replaces Equation B for the directed MHD:

$$h(M, T) = \frac{1}{p} \sum_{m_i \in M} \min_{t_j \in T} \|m_i - t_j\|, \quad (C)$$

where p is the number of points in M .

However, all HD reported variants do not address each point's unequal contribution. In practice, each point's prominence in representing a facial image will likely be different. In our research, we apply a new HD variant—significance-based multiview Hausdorff distance (SMVHD). This considerably improves the authentication process's robustness even with the introduction of nonrigid distortions to the facial image, such as when a person speaks.

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$$h_{SMVHD}(T, M) = \frac{1}{\sum_{k=1}^n \sum_{t_i^k \in T^k} \text{Sig}_{t_i^k m_j^k}} \times \sum_{k=1}^n \sum_{t_i^k \in T^k} (\text{Sig}_{t_i^k m_j^k} \cdot \min_{m_j^k \in M^k} \|t_i^k - m_j^k\|),$$

where $\text{Sig}_{m_i^k t_j^k} = \frac{1}{2}(\text{Sig}_{m_i^k} + \text{Sig}_{t_j^k})$ is the average significance (within the range $0 \dots \infty$) of point m_i^k and its corresponding point t_j^k .

We derive the significance as follows. We apply the *dynamic two-strip algorithm*¹² to detect dominant points, which are the points with high curvatures, on the facial edge curves. In the Dyn2S algorithm, we fit a strip to the left and right of each point on the curve and approximate the points inside each strip as a straight line (see Figure 3). The strip's orientation and width adjusts automatically, favoring longer and narrower strips. We compute each curvature's point as the angle

subtended by its two strips. A strip's *elongatedness* is defined as the ratio of its length and width. Then, we calculate a measure of merit based on the strips' lengths and widths, and the angle between the strips. We can compute a point's merit as $E^{left} \cdot S \cdot E^{right}$, where $S = |180^\circ - \theta|$ is the acuteness of the angle θ between the two strips, and E^{left} and E^{right} are the left and right strips' elongatedness. The algorithm chooses minimum and maximum strip widths.

Figure 2. Significance-based multiview Hausdorff distance matching.

Multiview authentication system

We developed an experimental access control system based on fusing multiple views of facial images using SMVHD. Figure 1 shows a possible application scenario of the system, where a stationary person stands at a designated position to have multiple facial images taken. We can obtain the multiple views either by installing multiple fixed cameras at the desired locations (three in our case) or by using a single camera that moves on a track. With suitable hardware components, you could use the system for other authentication purposes, such as online business transactions.

During enrollment, as shown in Figure 1a, we capture three views (frontal, three-quarter, and profile) as still images. Preprocessing isolates the facial area to reduce the effect of hair and clothing. For the profile image, preprocessing entails nose tip and chin detection,¹³ followed by facial area normalization, alignment, and cropping. For other images, the preprocessing procedure is the same except that we perform eye detection¹⁴ instead of nose tip and chin detection. We store the extracted model points in a database as M_X^k for person X with views $k = 1, 2, 3$.

During authentication, anyone who claims to be person X has multiple views captured as still images, which are preprocessed with the same procedure as in the enrollment. This results in T_X^k for the person claiming to be person X . Based on SMVHD matching of the stored model for person X (M_X^k), the system decides whether this is in fact person X . For generality, our system also permits a final decision made by combining results from other analysis modes (for example, speech). However, we haven't implemented this because we are interested in optimizing multiview facial analysis performance, which is essentially a single-modal operation.

We apply local maximum detection to select points of high curvature. An initial strip of minimal width (the dashed line in Figure 3) extends from P to encompass as many points as possible to one side. Its width is incremented and its orientation adjusts to include as many points as possible until it reaches the maximum strip width (the left solid-line strip). The elongatedness measure for each strip is recorded. We apply the same procedure to P 's other side and retain the left and right strips with the highest elongatedness measures. The algorithm chooses a subset of significant points using local maxima. It selects them in three steps. First, it eliminates points with small merit, as compared to their neighbors. Then, it reinstates a number of points to avoid over-elimination. It chooses the points from any points not covered by a strip selected in the first step. Finally, it deletes points that align approximately on a straight line, except for the curve's two endpoints. The remaining points are the feature points extracted.

This measure of merit provides an objective evaluation of each point's prominent

strength, and we can use it as a significance measure of the dominant point in the proposed distance measure. Thus, the significance measure is derived automatically as a by-product of the feature point detection algorithm.

Compared to other HD variants, where the contributions from all points are equal, every

$$\min_{t_j^k \in T^k} \|m_i^k - t_j^k\|$$

(that is, a matched pair's distance) in SMVHD is weighted by the average significance of m_i^k and t_j^k because its contribution to $h_{SMVHD}(M, T)$ is assumed to be proportional to the two matched points' significances. The same property applies to $h_{SMVHD}(M, T)$. In fact, SMVHD is symmetric with respect to M and T . So, matching M to T will yield the same result as matching T to M . Additionally, we can match multiple points in M to a single point in T and vice versa (see Figure 2). This introduces tolerance to nonrigid distortion into the distance measure.

Figure 3. Illustration of the dynamic two-strip algorithm.¹³ An initial strip (the dashed line) of minimal width extends from *P* to encompass as many points as possible to one side.

Performance analysis

Here, we analyze our system’s performance. Our experiments’ results have been very encouraging.

Modified HD and SMVHD matching

We compared MHD (see the “Face Recognition” sidebar) and SMVHD, using images from different sources: the *Stirling_faces*, *nott-faces-originals*,¹⁵ and images we took. *Stirling_faces* is a collection of 311 images of 35 persons. It contains 31 complete sets of images (16 females and 15 males), each with three poses (frontal, three-quarter, and profile) and three expressions (neutral, smiling, and speaking). Figure 4 show an example for one person in the database. Similarly, the *nott-faces-originals* collection contains 384 images with each face in four expressions (neutral, smiling,

surprise, and disgust) with a frontal view, two expressions (neutral and smiling) with a three-quarter view, and one frontal view wearing a bathing cap over hair. In this case, we selected 88 images of 20 individuals (neutral frontal with or without bathing cap, smiling frontal, neutral three-quarter, and smiling three-quarter). This collection poses two particular challenges. First, the algorithms (especially, SMVHD) must operate on fewer images (for example, without the profile view). Second, the bathing cap obviously causes more difficulty. We augmented these collections with 360 images of 40 individuals of our own.

We compared MHD and SMVHD’s matching results using these images. Table 1 summarizes the results. Our experiments show that SMVHD performs significantly better than MHD in terms of accuracy. We achieved a 100 percent match with faces without nonrigid distortions (neutral expressions). Even with nonrigid distortions (smiling and speaking), SMVHD still achieved very high matching accuracy. We also measured the computational times in these experiments. We used an SGI Octane workstation with a 300-MHz CPU and 512 Mbytes RAM. On average, SMVHD required 0.52 s per person (all three views), and MHD required 0.22 s, 0.19 s, and 0.12 s for the

Figure 4. One person’s facial images from the *Stirling* database.

TABLE 1
Comparisons of the accuracy of modified Hausdorff distance and significance-based multiview HD.

Expression	MHD			SMVHD
	Frontal view (%)	Three-quarter View (%)	Profile view (%)	All views, fused (%)
Neutral	96.5	96.0	90.0	100.0
Smiling	71.1	80.5	64.5	93.6
Speaking	87.1	80.6	58.1	93.5

Figure 5. Experimental protocol: Image capture for (a) training neutral expression, *n*, for enrollment and (b) testing *n* and speaking, *s*, for authentication. (Each of the 63 persons had frontal, *f*; profile, *p*; and three-quarter, 3/4, views taken.) (c) A leave-one-out and rotation scheme.

frontal, three-quarter, and profile views. So, the average computational time per person was about half a second in each case.

Authentication performance

In this experiment, we aimed to simulate real-life situations for access control as much as possible. This required a delay between images captured for the enrollment process and authentication. Our experimental protocol follows. Sixty-three volunteers took part—41 males and 22 females. During the enrollment process, each person had three images captured (frontal, three-quarter, and profile), all with

neutral expressions. One month later, we captured the images of the same 63 people for authentication. We took three shots of each person (frontal, three-quarter, and profile), first with a neutral expression, followed by nonrigid distortions caused by speaking (saying their name). Introducing nonrigid distortion would allow for mixed-mode processing with speech analysis if desired. We also randomly altered the illumination to simulate a typical real-life environment. We conducted our experiments in a laboratory with windows on one side, and we varied the mix of ambient sunlight with fluorescent lights.

We conducted the experiments using a “leave-one-out and rotation” scheme. For this, we labeled a person an “imposter,” with others acting as “clients.” The imposter attempted to be identified as one of the 62 clients. The number of times that each imposter gained access under someone else’s identity contributed to the FAR. The clients also tried to gain access under their own identity, contributing to the FRR. We obtain the FAR by dividing the number of imposter acceptances by the number of imposter claims; we obtain the FRR by dividing the number of client rejections by the number of client claims. Figure 5 diagrams the experimental protocol. Figure 6 gives a ROC plot for our experimental system.

Figure 6 shows that we can achieve an EER of about 0.022 even with the variation in illumination during authentication. This result far surpasses single-modal operations that rely on facial analysis reported elsewhere.^{11,16,17} In fact, this performance level already approaches those of multi-modal methods.¹¹ Even with nonrigid distortion caused by speaking during authentication, the EER of about 0.029 was still reasonably good.

Figure 6. Receiver operating characteristic plot for our experimental system.

Further research is underway to finetune our algorithm and to conduct more tests on the system.

In particular, we would like to measure our system's stability. Through a bootstrap process, we can leave out some views of each person during the enrollment process and subsequently present those unseen views during authentication. We can then repeat this process by leaving out an additional set of views. This should result in both an average score and a variance measure, which would let us better gauge the process's stability, especially when performed daily over a period of time. ■

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Useful Reading

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