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Biometric template selection and update: a case study in fingerprints

Umut Uludag[a], Arun Ross[b,*], Anil Jain[a]

[a] Department of Computer Science and Engineering, Michigan State University, East Lansing, MI 48824, USA
[b] Department of Computer Science and Electrical Engineering, West Virginia University, Morgantown, WV 26506, USA

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Abstract

A biometric authentication system operates by acquiring biometric data from a user and comparing it against the template data stored in a database in order to identify a person or to verify a claimed identity. Most systems store multiple templates per user in order to account for variations observed in a person's biometric data. In this paper we propose two methods to perform automatic template selection where the goal is to select prototype fingerprint templates for a finger from a given set of fingerprint impressions. The first method, called `DEND`, employs a clustering strategy to choose a template set that best represents the intra-class variations, while the second method, called `MDIST`, selects templates that exhibit maximum similarity with the rest of the impressions. Matching results on a database of 50 different fingers, with 200 impressions per finger, indicate that a systematic template selection procedure as presented here results in better performance than random template selection. The proposed methods have also been utilized to perform automatic template update. Experimental results underscore the importance of these techniques.

Keywords: Biometrics; Template selection; Template update; Fingerprints; Clustering; Prototype; Template aging

1. Introduction

A biometric authentication system uses the physiological (fingerprints, face, hand geometry, iris) and/or behavioral (voice, signature, keystroke dynamics) traits of an individual to identify a person or to verify a claimed identity [1]. A typical biometric system operates in two distinct stages: the enrollment stage and the authentication stage. During enrollment, a user's biometric data (e.g., fingerprints) is acquired and processed to extract a feature set (e.g., minutiae points) that is stored in the database. The stored feature set, labelled with the user's identity, is referred to as a template. In order to account for variations in the biometric data of a user, multiple templates corresponding to each user may be stored. During authentication, a user's biometric data is once again acquired and processed, and the extracted feature set is matched against the template(s) stored in the database in order to identify a previously enrolled individual or to validate a claimed identity. The matching accuracy of a biometrics-based authentication system relies on the stability (permanence) of the biometric data associated with an individual over time. In reality, however, the biometric data acquired from an individual is susceptible to changes due to improper interaction with the sensor (e.g., partial fingerprints, change in pose during face-image acquisition), modifications in sensor characteristics (e.g., optical vs. solid-state fingerprint sensor), variations in environmental factors (e.g., dry weather resulting in faint fingerprints) and temporary alterations in the biometric trait itself (e.g., cuts/scars on fingerprints). In other words, the biometric measurements tend to have a large intra-class variability. Thus, it is possible for the stored template data to be significantly different

* Corresponding author. Tel.: +1-304-293-0405; fax: +1-304-293-8602.

E-mail addresses: uludagum@cse.msu.edu (U. Uludag), ross@csee.wvu.edu (A. Ross), jain@cse.msu.edu (A. Jain).

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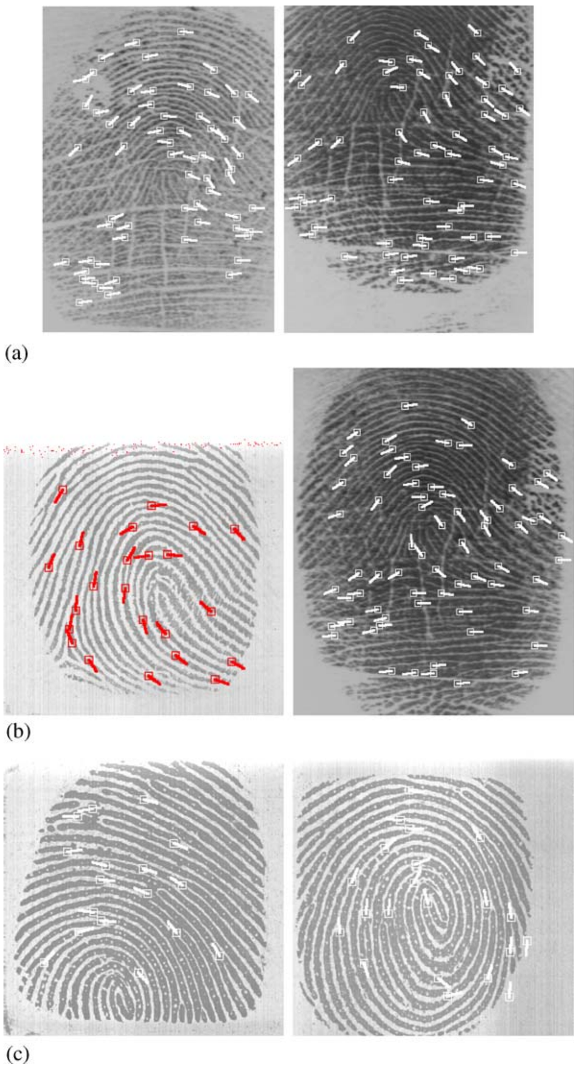


Fig. 1. Intra-class variation in fingerprints. (a) Two impressions of the same finger separated by a period of 6 weeks exhibiting difference in moisture content. (b) Two impressions of the same finger acquired using different sensors (solid-state and optical). (c) Two impressions of a fingerprint exhibiting partial overlap.

from those obtained during authentication (see Figs. 1–3), resulting in an inferior performance (higher false rejects) of the biometric system.

In order to account for the above variations, multiple templates, that best represent the variability associated with a user's biometric data, should be stored in the database. For example, one could store multiple impressions pertaining to different portions of a user's fingerprint in order to deal with the problem of partially overlapping fingerprints. Similarly, a user's face image acquired from multiple viewpoints may be stored in order to account for variations in a person's pose. There is a tradeoff between the number of templates, and the storage and computational overheads introduced by multiple templates. For an efficient functioning of a biometric system, the process of template selection has to be automated. However, there is limited literature dealing with the problem of automatic template selection in a biometric system. [1] In this paper we propose techniques to perform automatic *template selection*. The methods presented here attempt to represent the *variability* as well as the *typicality* observed in a user's biometric data. The proposed methods have also been utilized to perform automatic *template update*. Our experimental results indicate the importance of adopting a formal procedure to perform template selection and update. Although we consider a fingerprint-based biometric system as our test-bed, the techniques presented in this paper may be applied to other types of biometric traits (such as face and hand geometry) as well.

The rest of the paper is organized as follows. In Section 2 the two methods used to perform template selection have been described; in Section 3 the methodologies used to perform template update have been explained; Section 4 describes the experiments conducted to study the effectiveness of the proposed techniques; Section 5 summarizes the results of this work and provides future directions for research.

2. Template selection

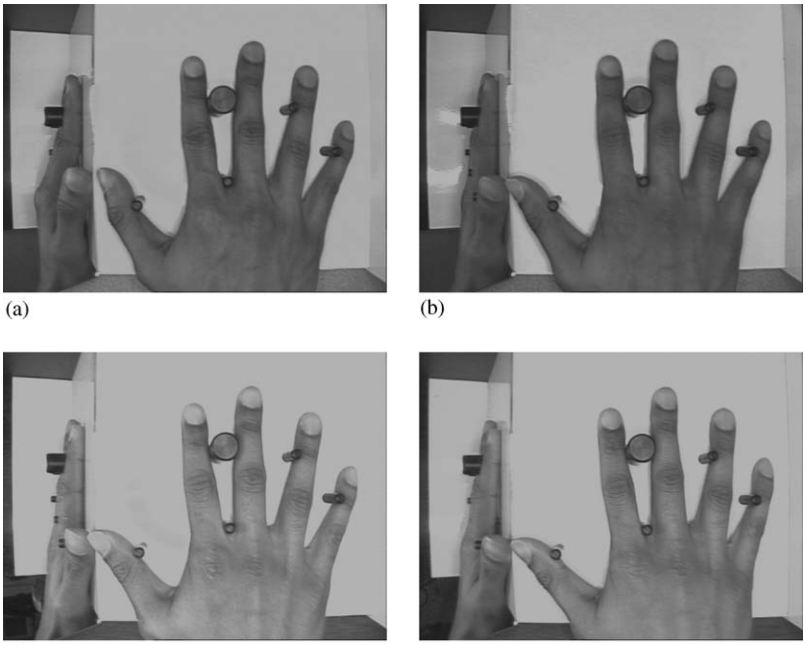
The problem of template selection with regard to fingerprints may be posed as follows: Given a set of N fingerprint images corresponding to a single finger, select K templates that 'best' represent the variability as well as the typicality observed in the N images, $K < N$. Currently, we assume that the value of K is predetermined. This systematic selection of templates is expected to result in a better performance of a fingerprint matching system compared to a random selection of K templates out of the N images.

It is important to note that template selection is different from template update. The term template update is used to refer to one of the following situations: (i) *Template aging*: Certain biometric traits of an individual vary with age. The hand geometry of a child, for example, changes rapidly during the initial years of growth. To account for such changes, old templates have to be regularly replaced/augmented with newer ones. The old templates are said to undergo aging. (ii) *Template improvement*: A previously existing template may be modified to include information obtained at a more recent time instance. For example, minutiae points may be added to, or deleted/modified from the template of a fingerprint, based on information observed in recently acquired impressions [3–5]. As another example, Liu et al. [6] update the eigenspace in a face recognition system via decay parameters that control the influence of old and new training samples of face images. Thus, template selection refers to

[1] Template selection has been studied in the context of other pattern recognition problems (see Ref. [2], for example).

(a) (b) (c)

Fig. 2. Intra-class variation associated with an individual's face image. Due to change in pose, an appearance-based face recognition system will not be able to match these three images successfully, although they belong to the same individual [12].



(a) (b) (c) (d)

Fig. 3. Hand images of an individual acquired over a period of 4 years using the same hand reader [13].

the process by which prototype templates are chosen from a given set of samples, whereas template update refers to the process by which existing templates are either replaced or modified. In the next section, we present techniques for template update, based on the template selection methods presented in this section.

We propose the following two methods for template selection:

Method 1 (DEND): In this method, the N fingerprint impressions corresponding to a user are grouped into K clusters, such that impressions within a cluster are more similar than impressions from different clusters. Then for each cluster, a prototype (representative) impression that typifies the members of that cluster is chosen, resulting in K template impressions. This technique, therefore, selects prototypes that represent the variability observed in the impressions.

To perform clustering, it is required to compute the (dis)similarity between fingerprint impressions. This measure of (dis)similarity is obtained by matching the minutiae point sets of the fingerprint impressions. Our matching algorithm is based on an elastic string matching technique [7], and it outputs a distance score indicating the dissimilarity of the minutiae sets being compared. We use a simple matching algorithm since our goal is to perform template selection, regardless of the characteristics of the matching algorithm.

Since our representation of the N fingerprint impressions is in the form of a $N \times N$ dissimilarity matrix instead of a $N \times d$ pattern matrix (d is the number of features), we use hierarchical clustering [8]. In particular, we use an agglomerative complete link clustering algorithm. The output of this algorithm is a dendrogram which is a binary tree, where each terminal node corresponds to a fingerprint impression, and the intermediate nodes indicate the formation of clusters (see Fig. 4).

The template set T, $|T| = K$, is selected as follows:

Step 1: Generate the $N \times N$ dissimilarity matrix, M, where entry (i, j), $i, j \in \{1, 2, \ldots, N\}$ is the distance score between impressions i and j.

Step 2: Apply the complete link clustering algorithm on M, and generate the dendrogram, D. Use the dendrogram D to identify K clusters.

Step 3: In each of the clusters identified in step 2, select a fingerprint impression whose average distance from the rest of the impressions in the cluster is minimum. If a cluster has only 2 impressions, choose any one of the two impressions at random.

Step 4: The impressions selected in step 3 constitute the template set T.

In Step 2, the algorithm automatically determines the threshold distance to cut the dendrogram and identify exactly K clusters. For example, for the dendogam given in Fig. 4, this distance is determined to be 644. We refer to the above algorithm as `DEND` since it uses the dendrogram to choose the representative templates. The algorithm selects prototypes that represent the *variability* observed in a user's data. Therefore, this algorithm is prone to selecting outliers.

Method 2 (`MDIST`): The second method sorts the fingerprint impressions based on their *average* distance score with other impressions, and selects those impressions that correspond to the K smallest average distance scores. Here, the rationale is to select templates that exhibit maximum similarity with the other impressions and, hence, represent typical data measurements. We refer to this method as `MDIST` since templates are chosen using a minimum distance criteria. The prototype set selected by this technique represents data that is likely to occur frequently. Thus, for every user:

Step 1: Find the pair-wise distance score between the N impressions.

Step 2: For the jth impression, compute its average distance score, d_j, with respect to the other $(N-1)$ impressions.

Step 3: Choose K impressions that have the smallest average distance scores. These constitute the template set T.

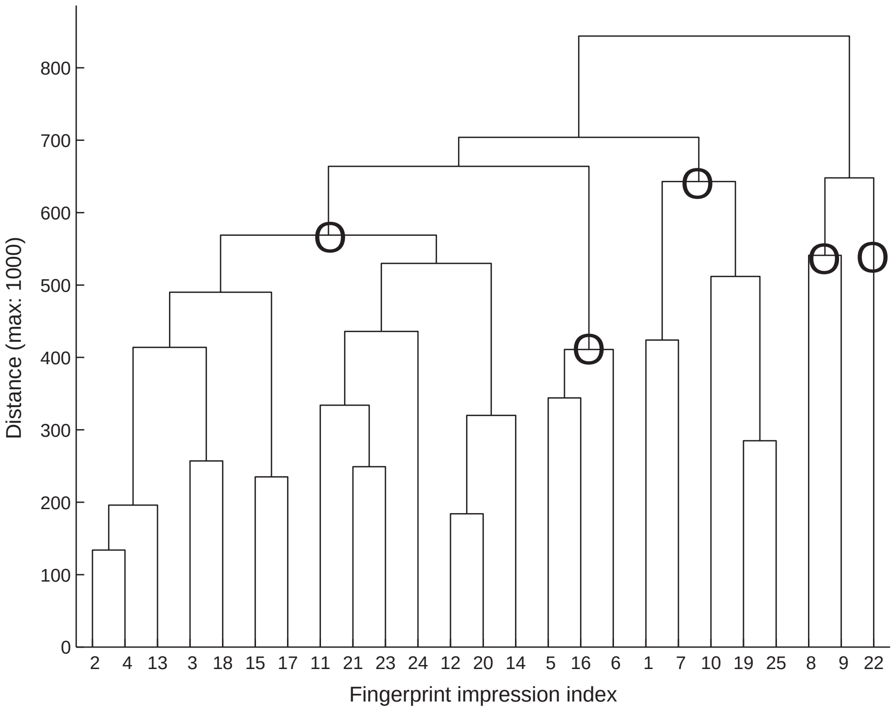


Fig. 4. Dendrogram generated using the 25×25 dissimilarity matrix of a finger. The circles on the subtrees indicate cluster formations for $K = 5$.

The choice for the value of K is application dependent. Larger K values would mean storing more templates per user, and this may not be feasible in systems with limited storage capacities. Moreover, in an identification system, matching a query (input) data with a large number of templates per user would be computationally demanding. Smaller K values, on the other hand, may not sufficiently capture the intra-class variability nor the typicality of the data, leading to inferior matching performance. Therefore, a reasonable value of K, that takes into account the aforementioned factors, has to be specified.

3. Template update

The methods presented in the previous section can be applied periodically in order to *update* the currently selected template set. In a biometric system, a user provides biometric data every time the authentication stage is invoked. Thus, newer samples of a user's biometric are made available over a period of time. This newly acquired data can be used to refresh the current template set in order to account for temporal changes that may occur in a person's biometric trait. We suggest two simple methods to perform template update using the newly acquired data.

In the first method, all current templates are replaced with templates selected from the newly acquired data set, thereby capturing temporal changes in the fingerprints (e.g., changes due to environmental conditions, sensor characteristics or subject's occupational characteristics). We call this method `BATCH-UPDATE` since the previously selected batch is discarded and only the newly acquired data is considered.

In the second method, both the current template set and the newly obtained data set are considered when performing template update. The template selection procedure is applied *after* augmenting the new data set with the current template set. This method is called `AUGMENT-UPDATE`. We provide experimental results pertaining to both these update methodologies in the next section.

The template selection and update procedure can be invoked on each user independently and is not affected by the variable number of biometric samples available for a user. Moreover, it is an off-line process that does not interfere with the real-time performance of a system. As a result, the procedure can be easily scaled to accommodate a large number of users.

4. Experimental results

In order to study the effect of automatic template selection and update on fingerprint matching, it is necessary to acquire several impressions per finger over a period of time. Standard fingerprint databases (e.g., FVC 2002 [9]) do not contain a large number of impressions per finger. Therefore, we collected 200 impressions each of 50 different fingers in our laboratory using the Identix BioTouch USB 200 optical sensor (255×256 images, 380 dpi). The data was acquired over a period of approximately four months with no more than 5 impressions of a finger per day. The 200 impressions of each finger were partitioned into two sets; the first 100 impressions (`DATA1`) were used to conduct the template selection experiments while the remaining 100 impressions (`DATA2`) were used in the template update experiments. Each of these two sets were further divided into training (first 25 impressions) and test (remaining 75 impressions) sets. These individual partitions were labelled as `TRAIN1`, `TEST1`, `TRAIN2` and `TEST2`.

4.1. Template selection

The template selection experiments were conducted using `DATA1`. The selection procedure was applied to images in `TRAIN1`, while the matching performance was evaluated using images from `TEST1`.

Fig. 4 shows the dendrogram obtained using the 25 fingerprint impressions of one finger. On setting $K = 5$, the resulting clusters and their prototypes as computed using the `DEND` algorithm are shown in Fig. 5; some clusters are seen to have only one member, suggesting the existence of outliers. The various prototypes are observed to have different regions of overlap with respect to the extracted minutiae points. The prototypes, for the same finger, computed using the `MDIST` algorithm are shown in Fig. 6.

In order to assess the matching performance of the proposed techniques (for $K = 5$), we match every image in `TEST1` (50 fingers, 75 impressions per finger) against the selected templates (5 per finger). When a test image is matched with the selected template set of a finger, 5 different distance scores are obtained. The mean of these scores is reported as the final matching score.[2] Thus, we obtain 187, 500 matching scores ($75 \times 50 \times 50$) using the selected template sets. Fig. 7(a) shows the receiver operating characteristic (ROC) curves representing the matching performance of the template sets selected using both the algorithms. The equal error rates (EER) of `DEND` and `MDIST` are observed to be 7.42% and 6.62%, respectively. Now, for the 50 fingers, there are a total of $\left(\binom{25}{5}\right)^{50} - 1$ *non-selected* template sets. It is computationally prohibitive to generate the matching scores and the ROC curves corresponding to all these permutations. Therefore, we chose 53, 130 permutations (assuming that the impression indices in the template set of all the 50 fingers is the same) and computed their EER. The histogram of EER values is shown in Fig. 7(b), where the minimum, mean and maximum EER values are 6.12%, 7.89% and 10.31%, respectively. In this histogram, the vertical lines indicate the EER values corresponding to the `DEND` and `MDIST`

[2] Other techniques to combine matching scores can be found in Ref. [10].

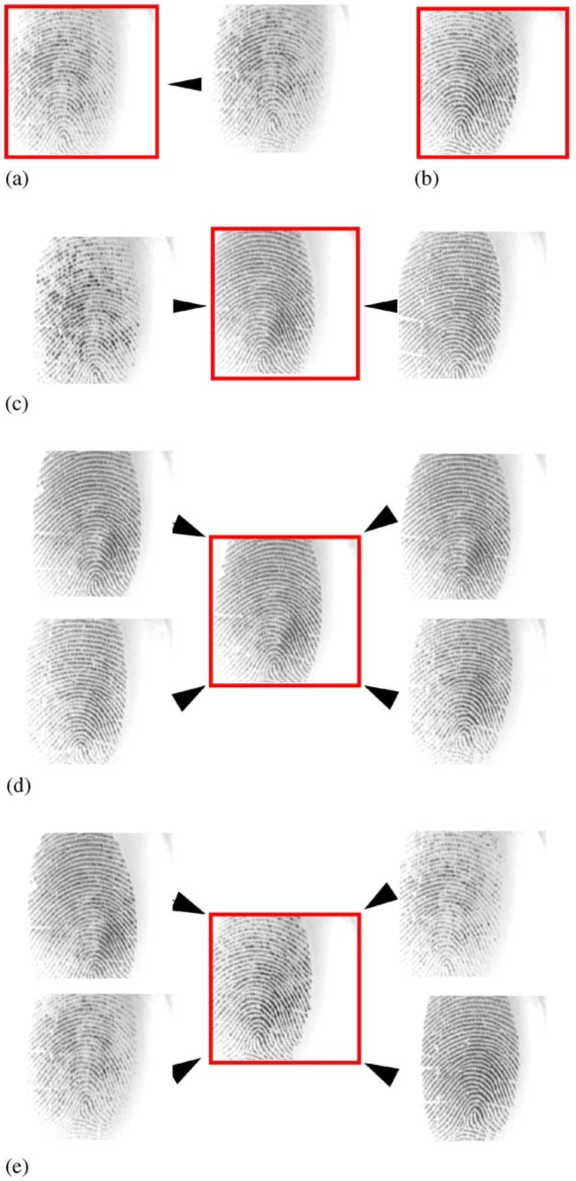


Fig. 5. The cluster membership ($K = 5$) for the dendrogram shown in Fig. 4. At most 5 members are indicated for each cluster. The prototype template in each cluster is marked with a thick border. Note that the cluster in (b) has only one member.

algorithms. The percentage of non-selected template sets that have a lower EER than the template sets selected with the proposed methods is 30.3% and 1.6%, for DEND and MDIST, respectively, thereby suggesting that systematic template selection is better than random selection.

We see that the MDIST method of template selection leads to a better matching performance compared to the DEND method of selection. This may be attributed to the fact that MDIST selects a template set consisting of images that exhibit maximum similarity with other impressions; therefore, the probability of them being correctly matched with impressions of the same finger is fairly high. On the other hand, the DEND method is prone to selecting impressions that are outliers thereby increasing the probability of false rejects. However, both methods are essential due to the complementary nature of the template set that they select.

To further understand the differences and similarities between the template sets selected by the DEND and MDIST methods, we calculated the number of common impressions selected using these two methods (for $K = 5$). The minimum, average (over all 50 users) and the maximum values for this number is found to be 0, 1.54 and 4, respectively. Since, on the average, 1.54 out of a possible 5 impressions are common in the selected sets, the difference in performance between the two techniques stems from the remaining members of the respective sets.

Table 1 lists the impressions of a finger that were selected as templates using the DEND and MDIST algorithms at different K values. The impression index indicates the acquisition time of the impressions—a lower index referring to an earlier time instance. We see that there is no direct relationship between an impression index and its choice as a template. Fig. 8 shows the EERs of the two methods at different values of K. A good choice for K (that can balance system performance with the computational/storage overheads) could be established by observing the knee point in the respective error curves (e.g., $K = 5$ for DEND). However, a more formal method needs to be developed for determining the value of K for a specific application.

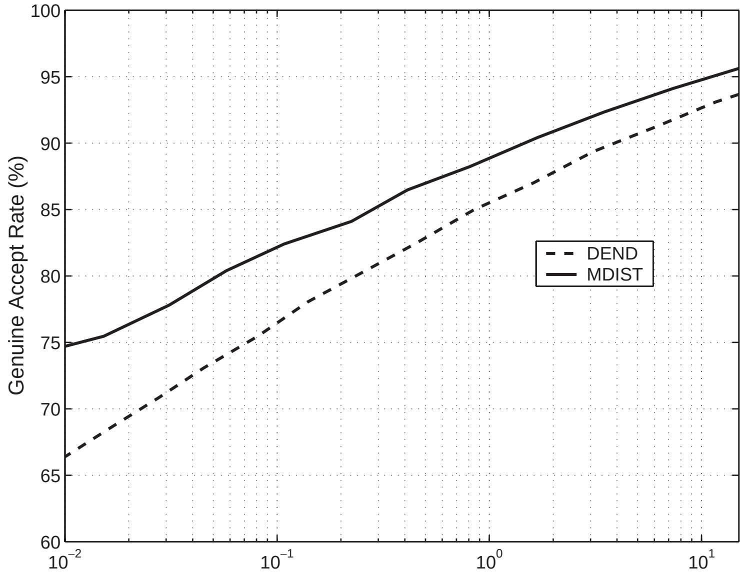
4.2. Template update

In this subsection, we report the system performance of the BATCH-UPDATE and AUGMENT-UPDATE methods. Observe that both these update techniques implicitly rely on the template *selection* procedures described earlier. They differ only in the choice of the data set on which template selection is performed. To demonstrate the importance of template update, we report the matching performance before and after the update process. We assume that the current template set of a finger consists of images from TRAIN1.

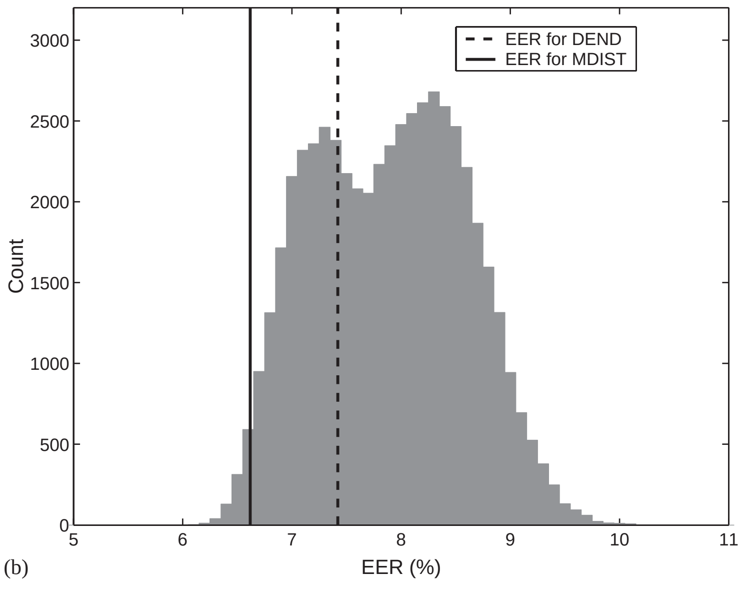
In the BATCH-UPDATE method, template selection was performed on TRAIN2 after completely discarding the template set extracted from TRAIN1. In the AUGMENT-UPDATE method, on the other hand, images from TRAIN2 were first augmented with the 5 current templates, and template selection was performed on the augmented set. Both the update techniques selected 5 templates from their respective candidate sets. The matching performance of the two update techniques was evaluated using data set TEST2. Fig. 9 shows the ROC curves indicating the performance before template update (i.e., templates selected from TRAIN1

(a) (b) (c) (d) (e)

Fig. 6. The prototype templates of a finger selected using the MDIST algorithm. The average distance measures for these are (a) 425, (b) 429, (c) 431, (d) 441, and (e) 452.



(a)



(b)

Fig. 7. (a) The ROC curves for the DEND and MDIST algorithms on a database of 50 fingers with 75 impressions per finger used in the test phase. (b) The EER histogram for the non-selected sets. The EER of the DEND and MDIST algorithms are also indicated.

Table 1
The impression indices of selected templates for a finger at different values of K

K	DEND	MDIST
1	2	2
3	4, 8, 25	2, 4, 13
5	4, 5, 9, 22, 25	2, 3, 4, 12, 13
7	2, 5, 7, 9, 19, 22, 23	2, 3, 4, 12, 13, 21, 23
9	2, 5, 7, 8, 9, 19, 20, 22, 23	2, 3, 4, 12, 13, 20, 21, 23, 25

were tested on TEST2) and after incorporating the template update procedures. Table 2 lists the EERs of both the update methods based on the selection technique (DEND and MDIST) that was employed. It is seen that both the update methods result in substantial improvement in matching performance.

We observe from the ROC curves and EER values that AUGMENT-UPDATE results in better performance than BATCH-UPDATE. This is because in AUGMENT-UPDATE we give the previously selected templates a chance to compete for reselection. This can help in retaining long-term trends in the characteristics of the fingerprint impressions leading to the observed improvement in performance. In AUGMENT-UPDATE, the average number of reselected templates (the average is taken over 50 users) was found to be 1.5 and 0.62 using the DEND and MDIST methods, respectively.

5. Discussion and future work

A systematic procedure for template selection and update is critical to the performance of a biometric system. In this paper we have proposed two techniques to perform template selection in the context of a fingerprint matching system. Both techniques are based on the distance score between pairs of fingerprint impressions originating from the same finger. The first method called DEND utilizes a clustering scheme to detect prototype impressions. The template set selected by this technique captures the variability observed in a user's fingerprint image. The second method called MDIST ranks the fingerprint impressions based on their average distance from the other impressions, and then selects impressions whose average distance is the least. Thus, it aids in selecting a template set that exhibit maximum similarity with the other impressions. Our experiments demonstrate that a systematic template selection procedure results in better performance than random template selection; it was also observed that the MDIST technique results in better performance than DEND. Currently, we are studying ways to effectively combine the two techniques in order to further improve system performance. We are also considering methods to determine the value of K automatically.

We have also proposed two template update methods that refresh the current template set based on newly acquired biometric data. The update methods implicitly rely on the template selection process. The AUGMENT-UPDATE technique performs template selection by considering both the current

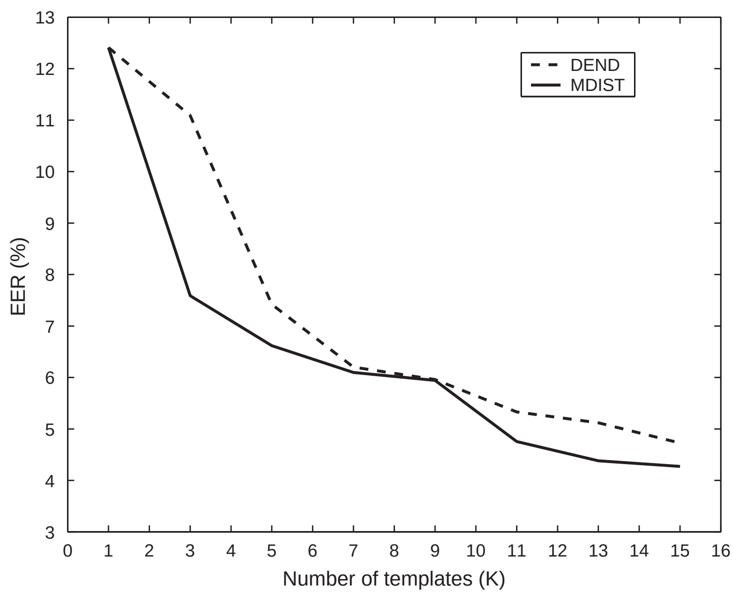


Fig. 8. The EER of the fingerprint matcher plotted as a function of K.

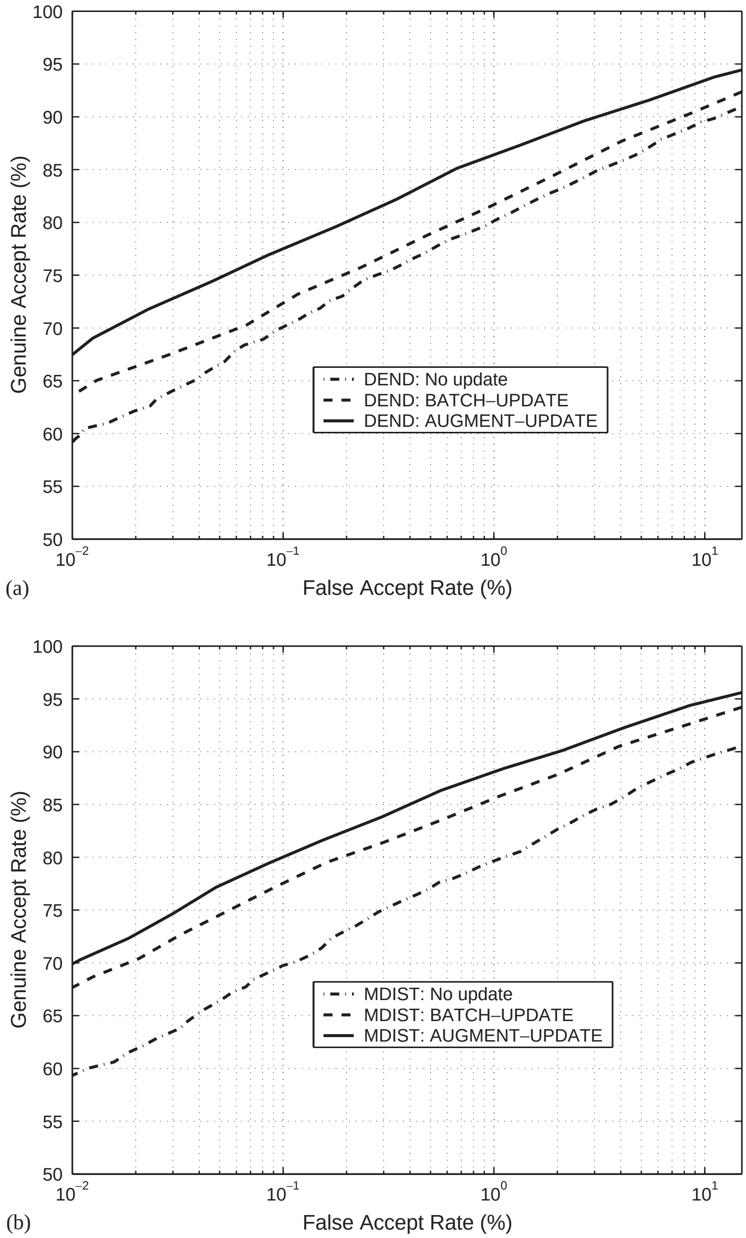


Fig. 9. ROC curves showing improvement in performance when the `BATCH-UPDATE` and `AUGMENT-UPDATE` procedures are incorporated. In (a) the `DEND` method of template selection was used, while in (b) the `MDIST` method was employed.

template set as well as the newly acquired data set. The `BATCH-UPDATE` technique, on the other hand, considers only the newly acquired data set and completely discards the current template set. Both the update methods were shown to improve the matching performance of the system. Our experiments indicate that `AUGMENT-UPDATE` yields better matching performance than `BATCH-UPDATE`.

It must be mentioned that the template selection and update techniques described here are based on the distance measure (scores) between pairs of fingerprint impressions. We have, therefore, adopted a featureless approach to clustering [11]. Hence, if a different fingerprint matching algorithm is used, a different set of prototype impressions is likely to be obtained. We are developing alternate techniques that would operate on the raw images in order to detect prototype impressions. We are also in the process of testing our techniques on other biometric modalities as well (viz., face and hand geometry).

Table 2
EER values before and after incorporating the template update procedure

Update technique	EER (%)
DEND method	
No update	10.61
BATCH-UPDATE	9.55
AUGMENT-UPDATE	7.37
MDIST method	
No update	10.32
BATCH-UPDATE	7.69
AUGMENT-UPDATE	6.31

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About the Author—UMUT ULUDAG received B.S. and M.S. degrees in Electrical and Electronics Engineering from Bogazici University, Istanbul, Turkey in 1999 and 2001, respectively. He was a researcher in Marmara Research Center, Turkey, from 1999 to 2001. He is now a Ph.D. student in Department of Computer Science and Engineering, Michigan State University, East Lansing, MI. His research interests include biometrics, pattern recognition, watermarking, multimedia, image processing and computer vision. He is a member of the IEEE.

About the Author—ARUN ROSS is an Assistant Professor in the Lane Department of Computer Science and Electrical Engineering at West Virginia University. Ross received his B.E. (Hons.) degree in Computer Science from the Birla Institute of Technology and Science, Pilani (India), in 1996. He obtained his M.S. and Ph.D. degrees in Computer Science and Engineering from Michigan State University in 1999 and 2003, respectively. Between July 1996 and December 1997, he worked with the Design and Development group of Tata Elxsi (India) Ltd., in Bangalore. He also spent three summers (2000–2002) with the Imaging and Visualization group at Siemens Corporate Research, Inc., Princeton, working on fingerprint recognition algorithms. His research interests include statistical pattern recognition, image processing, computer vision and biometric authentication.

About the Author—ANIL JAIN is a University Distinguished Professor in the Departments of Computer Science & Engineering and Electrical and Computer Engineering at Michigan State University. His research interests include statistical pattern recognition, exploratory pattern analysis, Markov random fields, texture analysis, 3D object recognition, medical image analysis, document image analysis and biometric authentication. Several of his papers have been reprinted in edited volumes on image processing and pattern recognition. He received the best paper awards in 1987 and 1991, and received certificates for outstanding contributions in 1976, 1979, 1992, 1997 and 1998 from the Pattern Recognition Society. He also received the 1996 IEEE Transactions on Neural Networks Outstanding Paper award. He is a fellow of the IEEE, ACM, and International Association of Pattern Recognition (IAPR). He has received a Fulbright Research Award, a Guggenheim fellowship and the Alexander von Humboldt Research Award. He delivered the 2002 Pierre Devijver lecture sponsored by the International Association of Pattern Recognition (IAPR). He holds six patents in the area of fingerprint matching.