Index Codes for Multibiometric Pattern Retrieval

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***Abstract*—In a biometric identification system, the identity corresponding to the input data (probe) is typically determined by comparing it against the templates of all identities in a database (gallery). Exhaustive matching against a large number of identities increases the response time of the system and may also reduce the accuracy of identification. One way to reduce the response time is by designing biometric templates that allow for rapid matching, as in the case of IrisCodes. An alternative approach is to limit the number of identities against which matching is performed based on criteria that are fast to evaluate. We propose a method for generating fixed-length codes for indexing biometric databases. An index code is constructed by computing match scores between a biometric image and a fixed set of reference images. Candidate identities are retrieved based on the similarity between the index code of the probe image and those of the identities in the database. The proposed technique can be easily extended to retrieve pertinent identities from multimodal databases. Experiments on a chimeric face and fingerprint bimodal database resulted in an 84% average reduction in the search space at a hit rate of 100%. These results suggest that the proposed indexing scheme has the potential to substantially reduce the response time without compromising the accuracy of identification.**

***Index Terms*—Biometrics, feature extraction, image retrieval, indexing, pattern matching.**

I. Introduction

THE use of multiple biometric sources for human recognition, referred to as *multibiometrics*, mitigates some of the limitations of unimodal biometric systems by increasing recognition accuracy, improving population coverage, imparting fault-tolerance, and enhancing security [1]. The number of multibiometric systems deployed on a national scale is increasing (Table I) and the sizes of the underlying databases are growing. These databases are used extensively, thereby requiring efficient ways for searching and retrieving relevant identities.

Searching a biometric database for an identity is usually done by comparing the probe image against *every* enrolled identity in the database and generating a ranked list of candidate identities. Depending on the nature of the matching algorithm, the matching speed in some systems can be slow. New representation schemes that allow for faster search and, therefore, shorter response time are needed.

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TABLE I
EXAMPLES OF LARGE-SCALE MULTIBIOMETRIC SYSTEMS THAT HAVE BEEN EITHER PROPOSED OR DEPLOYED

Program name	**Biometric modalities**
US-VISIT [2]	Face and 10 fingerprints
National Identity Cards [3]	Face, fingerprints, signature
Bangladesh voter registration [4]	Face and 4 fingerprints
FBI database [5]	10 fingerprints
US PIV Cards [6]	2 fingerprints
India UID Card [7]	Face, irides, 10 fingerprints

The retrieval of a small number of candidate identities from a database based on the probe data is known as database *filtering*. Filtering can be accomplished by using classification or indexing schemes. In a classification scheme, identities in the database are partitioned into several classes. Only the identities belonging to the same class as that of the probe image are retrieved during the search process for further comparison. This approach has two main limitations: 1) it assumes that each identity can be unambiguously assigned to a single class; and 2) the distribution of identities across classes may be uneven resulting in inefficient classification.

In contrast, the goal of an indexing scheme is to assign a unique index value to every identity in the database. However, the index value of the probe image may not be identical to that of the corresponding identity in the database because the process of biometric acquisition and processing is susceptible to noise. Therefore, the retrieval scheme has to employ some type of neighborhood search in the index space. An efficient indexing algorithm retrieves a small number of candidate identities based on similarity measures that can be computed quickly. An important advantage of indexing techniques is that they do not create "boundaries" among the continuously distributed templates.

The process of indexing introduces additional computations in order to build index codes. Indexing can be made more efficient by organizing the index codes of the database in a tree-structure, thus avoiding a brute-force search. Examples of tree-structures used in biometric retrieval include kd-trees [8], [9], R+ trees [10], and B+ trees [11]. Tree structures are useful when the similarity measure used to compare index codes (viz., vectors) satisfies the metric property. Alternately, for similarity measures based on dot products, partial computation based on only a few elements of the index code can improve the speed of retrieval [12].

Multimodal biometric systems can employ cascading techniques to speed up the filtering process [10], [13]. In this approach, exhaustive matching is rapidly performed using a modality that has a fast matcher in order to narrow the search space of potential identities. The final identification is then conducted in the reduced search space using a different modality that has a better matching accuracy. Another approach, applicable to algorithms that employ subspace analysis, involves using numerical indexing on the projection coefficients [14].

We present a method for indexing multimodal biometric databases based on index codes generated by a biometric matcher. The indexing mechanism is executed separately for each modality and the results are combined into a final list of potential candidates. The proposed indexing technique relies on the use of a *small* set of reference images for each modality. A modality-specific index code is generated by matching an input image against these reference images, resulting in a set of match scores. During identification, the index code of the input image is compared to the index codes of the enrolled identities in order to find a set of potential matches. The index codes of multiple modalities are fused to improve the accuracy of indexing resulting in a robust and efficient indexing system. This approach relies on a matcher, which is an integral part of every automated biometric identification system. Because the generated index codes are compact and their (dis)similarity can be computed rapidly, the approach has low storage requirements and can improve the system response time even for small databases (e.g., one having 1000 subjects).

This manuscript is organized as follows. Section II presents a brief review of previous research on indexing and classification of biometric databases. Identification techniques that use reference data are also discussed. Section III describes the proposed indexing methodology and how it improves computational time. Indexing multimodal databases using two different fusion techniques is discussed in Section IV. The effect of various indexing parameters on overall performance is studied in Section V. The experimental configuration is summarized in Section VI. The performance of the proposed scheme is presented in Section VII. Section VIII includes conclusions and directions for future work.

II. Related Work

A. Fingerprint Indexing

The problem of fingerprint classification has been studied extensively. The first published fingerprint classification method, the Henry classification system [15], was based on the spatial configuration of singular points present in fingerprint patterns. Because of problems with occlusion, noise, and the potential lack of precision in locating singular points, more recent fingerprint indexing and classification techniques are based on minutiae points. The geometric properties of triangles constructed from minutiae points were first utilized to index fingerprints by Germain *et al.* [16], and later improved and extended by Bebis *et al.* [17] and Bhanu and Tan [18]. Fingerprint indexing using ridge orientation was proposed by Lumini *et al.* [19] and Cappelli *et al.* [20]. More recent techniques exploit both minutiae points and ridge orientation for indexing fingerprints [21], [22].

The indexing methods listed above require the application of image processing techniques which are specific to the indexing method. To avoid the complexity of designing new feature extraction routines, Maeda *et al.* [23] developed a retrieval method based on match scores. They adopted a sequential search process in which filtering was performed based on the correlation between the set of match scores that were already computed for the probe and the corresponding match scores for the images in the database that were not yet visited. In this technique, a matrix that contains the pairwise match scores of *all* images in the database has to be permanently stored and updated for each newly enrolled identity. A drawback of this approach is that storing the matrix of match scores for a database containing millions of images can be impractical.

B. Face Indexing

Indexing methods for face databases usually focus on a specific recognition algorithm. The approach of Lin *et al.* [24] is based on the classical eigenface method and uses the coefficients of projection to rank the database images with respect to each eigenface. The probe is ranked in the same way and a local search is performed for each eigenface to find the database image that is closest to the probe. Thus, the reduction in the search space depends on the number of eigenfaces used.

Another approach for face indexing relies on the use of small binary images obtained from an edge detection filter. The goal is to reduce dimensionality and allow faster comparisons during the search-and-retrieval stage. This technique was first proposed by Takacs [25], who applied the Sobel operator on mug-shot face images and used a modified Hausdorff distance to compare the resulting binary images. Compact binary codes were also used by Torralba *et al.* [26] for fast retrieval of face images from online databases.

A combination of classification and indexing was proposed by Perronnin and Dugelay [27]. A face database was split into a predefined number of classes by applying a clustering technique on parametric models of the enrolled faces. However, instead of performing classification by assigning the probe to a specific cluster, the set of distances between the probe and the centroid of each cluster was used as an index vector. Retrieval was based on the similarity among index vectors. The low-dimensionality of the index vectors and the fast computation of the similarity metric reduced the computational cost for the overall identification process but with a 5% loss in identification accuracy.

C. Indexing Using Match Scores

Reducing the dimensionality of the biometric template by using a set of distance (or similarity) scores to a fixed set of templates has been used in speaker recognition. Sturim *et al.* [28] compared each enrolled speaker against a fixed set of speaker models (called anchor models). The resulting set of scores was used as a projection of the speaker in the space defined by the anchor models. Retrieval was based on the distances between the probe and the enrolled speakers in the projection space. The calculation of these distances is much faster compared to conventional speaker matching schemes that utilize Gaussian mixture models. This technique led to a major improvement in computational cost with only a small decrease in identification rate when used to reduce the size of the database prior to identification. More recent studies improved the method of anchor models by imposing constraints on the set of anchor models in order to derive an optimal projection space [29] and appropriate distance measures [30], [31]. Sakata *et al.* [32] used a similar approach to create a secure fingerprint identification system, which did

TABLE II
ADVANTAGES AND DISADVANTAGES OF THE PROPOSED TECHNIQUE COMPARED TO OTHER INDEXING METHODS

Proposed technique	Other methods
Pros	
1) Can be applied to any biometric modality.	To the best of our knowledge, the technique proposed by Maeda et al [23] is the only published indexing approach that is modality-independent, but is prohibitive for use on large databases and has not been designed for multimodal databases.
2) Does not involve additional image processing and the associated manual tuning of parameters.	Modality-specific indexing algorithms often require complex image processing routines in addition to ones used for matching (e.g., singular point detection for fingerprints.)
3) Does not require training and is parameter-free.	State-of-the-art indexing techniques have to be tuned to the image resolution, magnitude of noise during image acquisition, and other properties of the enrolled images.
4) Applicable to databases storing only a single image for each modality of each individual.	Some indexing methods require multiple images of each subject.
5) Easy to extend to multi-modal databases.	
Cons	
1) Not expected to be efficient on small databases in operational scenarios, i.e., containing fewer than 1000 subjects.	Conventional indexing methods are applicable to small databases.
2) Dependent on the matcher used.	
3) May not achieve state-of-the-art indexing performance for some biometric modalities but can be easily ported for use on multimodal databases.	Techniques designed specifically for a certain modality may achieve better performance on unimodal databases.

not store the images of the enrolled individuals. To achieve a reliable identification performance, the original approach was modified by creating a set of anchor models for each enrolled individual and keeping multiple images per individual in the database.

We propose an indexing method that is similar to the anchor models approach and can be applied to any biometric modality. This is achieved by using the matcher inherent in the biometric system to create index codes (index vectors). Dimensionality reduction is not applied to the index codes. Instead, a small number of reference images, which form the basis of the index codes, are selected to ensure that the variance among the index codes is large. In contrast to the original approach of anchor models, our method uses raw image data and does not require training. Beside being applicable to any biometric modality, this indexing method can be easily incorporated into any existing biometric identification system. We demonstrate how the information available in multimodal biometric databases can be used to achieve fast retrieval and low error rates, even when each individual is enrolled with a *single image* for each modality. The creation of an index code involves matching the input image to a set of reference images. Therefore, depending on the image quality and the accuracy of the matcher, the proposed indexing method may not be advantageous for indexing small databases. A reasonable speedup in identification time can be achieved only when the size of the database is several times larger than the size of the reference set. The properties of the proposed method are summarized in Table II.

III. INDEX CODES FROM IMPOSTOR MATCH SCORES

The proposed indexing technique can either employ the biometric matcher that is already present in the biometric system or use another independent matcher. Index codes are generated for each modality using the corresponding matcher. During retrieval, the index code of the probe is compared against those in the gallery using a similarity measure to retrieve a list of candidate identities for biometric matching.

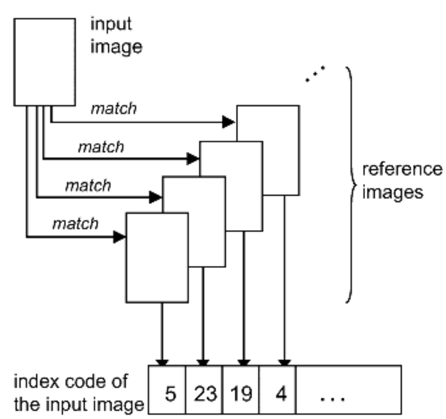

Fig. 1. Generation of an index code. An input image is matched against a set of reference images. The set of resulting match scores constitutes the index code of this input image.

A. Indexing a Single Modality

In this section, the face modality is used as an example to illustrate the process. However, the inferred properties are applicable to the fingerprint modality (as observed in our experiments) and perhaps to other biometric modalities as well.

Let $\mathcal{R} = \{r_1, r_2, \ldots, r_n\}$ be a set of face images, which we call *reference images*, and $\mathcal{S}_x(\mathcal{R}) = \{s(x,r_1), s(x,r_2), \ldots, s(x,r_n)\}$ be the set of match scores obtained when face image x is compared to each reference image in $\mathcal{R}$. We refer to $\mathcal{S}_x(\mathcal{R})$ as the *index code* of image x. In other words, the index code of an image is the list of its match scores against the reference images (Fig. 1). The proposed scheme can also be interpreted geometrically as shown in Fig. 2. From this perspective, the reference images may be viewed as "basis" vectors in the original feature space.

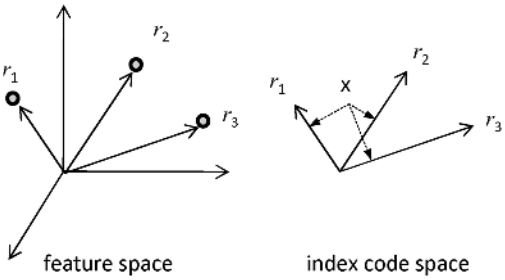

Fig. 2. Geometric interpretation of the proposed indexing approach. The reference images may be viewed as "basis" vectors in the original feature space. Therefore, the index code of an image X, may be viewed as the projection of X onto the "basis" vectors. The original feature space may not have a trivial geometric interpretation (e.g., the feature vectors may not be of fixed length). Therefore, to enable fast comparison, the match scores between X and the "basis" vectors are used to construct index codes.

The premise of our method is that if two images x and y belong to the same identity, then their index codes $\mathcal{S}_x(\mathcal{R})$ and $\mathcal{S}_y(\mathcal{R})$ are likely to be similar or $\mathcal{D}(x,y) \leq T$, where T is a predefined threshold and $\mathcal{D}$ is a distance measure. In contrast, if the images x and y belong to different individuals, then it can be expected that $\mathcal{D}(x,y) > T$.

During identification, the indexing system first computes the index code $\mathcal{S}_x$ of the probe x. Then it outputs all enrolled identities whose index codes are within a certain distance T from $\mathcal{S}_x$. Appropriate distance metrics are discussed in Section V-A.

When k modalities are available, the architecture of the proposed indexing scheme is defined by the k ordered sets of reference images (one set for each modality) and the k thresholds that specify the minimum similarity value needed to include an enrolled identity in the candidate list. The number of reference images for each modality can be different. The k index codes for each enrolled identity are stored in the database and used in a fusion framework during the retrieval process.

B. Conditions to Achieve Speedup

The retrieval process performs an exhaustive search across the index codes of the enrolled identities. Thus, an improvement in the speed of identification is possible only if the search space is substantially reduced and if the distance between two index codes can be computed in a fraction of the time needed to match two biometric templates.

Let P be the fractional reduction in the number of candidate identities achieved by the indexing scheme when applied on a database of size M. Let n denote the dimensionality of the index code. The overall computation time of the identification system can be approximated by the sum of the n matching operations between the input image and the reference images, the M operations for computing the distances between the index codes of the probe and the enrolled identities, and the $P * M$ matching operations required for the final identification. Similarly, the time needed for identification without indexing consists of M matching operations. If t_m is the time needed to perform a single matching operation and t_ρ is the time needed to compute the distance between two index codes, we are interested in determining the values of n, M, t_m, and t_ρ that will reduce the overall response time, i.e., we determine the conditions under which the following inequality holds:

TABLE III
BOUND FOR THE MINIMUM DATABASE SIZE FOR ACHIEVING IMPROVEMENT IN IDENTIFICATION SPEED. P IS THE FRACTIONAL REDUCTION IN THE SIZE OF THE DATABASE DUE TO INDEXING. α IS THE RATIO OF THE TIME TAKEN TO COMPARE TWO INDEX CODES TO THAT OF COMPARING TWO BIOMETRIC TEMPLATES

α	$\mathbf{P = 0.5}$	$\mathbf{P = 0.25}$	$\mathbf{P = 0.1}$
0.1	625	385	313
0.01	510	339	281
0.001	501	334	278

$$M\,t_m > n\,t_m + P\,M\,t_m + M\,t_\rho \quad (1)$$

$$M > \frac{n}{1-P-\alpha}, \quad P+\alpha < 1 \quad (2)$$

where $\alpha = t_\rho/t_m$.

The number of operations required for matching two biometric templates (at least for face and fingerprints) can be an order of magnitude larger than the computation of a similarity metric. Therefore, lets assume that $\alpha = 0.1$. If $n = 250$ (as in our experiments) and $P = 0.5$, then inequality (2) becomes $M > 625$. In other words, a reduction in the identification time will be achieved for databases storing at least 625 identities. The minimum database sizes for different values of P and α are shown in Table III. These results indicate that the value of P has a strong effect on the potential speedup. For large-scale databases, the most significant term in inequality (1) becomes $P * M * t_m$ and the speedup becomes almost linearly dependent on the ratio between the size of the candidate list and the size of the database.

IV. INDEX CODES FOR MULTIMODAL DATABASES

There is an inherent trade-off between the total number of retrieved candidates and the number of *correctly* retrieved candidates. Fusion schemes are often useful for narrowing down the total number of retrieved candidates and/or increasing the number of correctly retrieved candidates. In biometric identification, it is crucial that the correct identity is in the candidate list even if this results in a longer list. We propose two fusion techniques that use the information from multiple modalities in a complementary manner. Index codes are stored separately for each modality thereby making the indexing scheme flexible in including more modalities or excluding a certain modality. The ability to exclude a modality from the indexing process is valuable when prior knowledge indicates that a certain modality is unreliable or when data for a modality are missing. Our general approach for indexing multimodal databases is shown in Fig. 3.

A. Concatenation of Index Codes

Let $S_x(\mathcal{R}^i) = \{s(x^i, r_1^i), s(x^i, r_2^i), \ldots, s(x^i, r_n^i)\}$ be the index code of identity x, where i denotes the modality, r_j denotes the jth reference image in this modality, and $s(a,b)$ denotes the match score between a and b. The fused index code $\mathcal{F}_x$ is obtained by concatenating the index codes from different modalities: $\mathcal{F}_x = \{s(x^1, r_1^1), \ldots, s(x^1, r_n^1), s(x^2, r_1^2), \ldots, s(x^2, r_n^2)\}$.

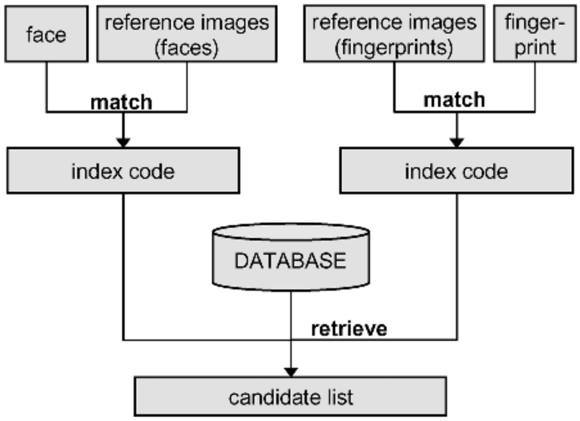

Fig. 3. Indexing two modalities. Two index codes are generated separately, one for each modality. The information from the two modalities is combined during retrieval.

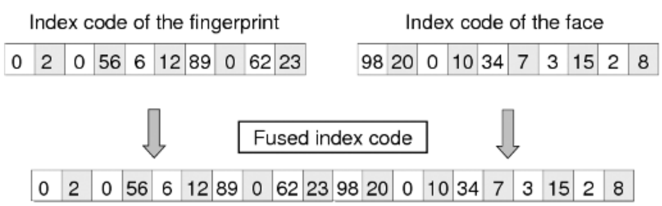

Fig. 4. Fusion by concatenation of index codes.

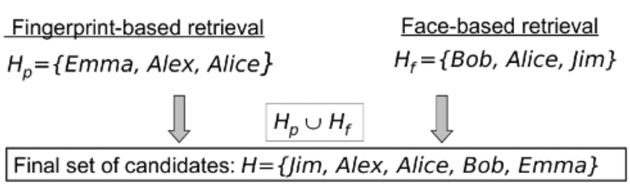

Fig. 5. Fusion by union of candidate lists.

Fig. 4 illustrates this process schematically. Retrieval using the fused index code is performed as for a single modality.

This fusion scheme results in longer index codes. Ideally, using longer index codes results in larger variances among them—this is desirable. One weakness of this fusion scheme is that poor indexing performance due to one of the modalities can negatively affect the overall performance of indexing.

B. Union of Candidate Lists

Another fusion mechanism is to combine the lists of candidate identities output by each modality. Let C^i be the set of retrieved identities according to modality i. The final set of identities retrieved by the indexing will be $\mathcal{C} = \bigcup_{i=1}^{k} C^i$ as shown in Fig. 5. This fusion scheme has the potential to increase the chances of finding the right identity in C even if the right identity is not located in some of the C^i's. Thus, poor indexing performance of one modality would have a smaller effect on the overall indexing performance. This approach fails only when the right identity is not retrieved by any of the k modalities. Intersection of the identities in the candidate lists is another option for indexing multimodal databases but is not discussed in this paper due to its inferior performance [33].

V. Parameters of the Proposed Indexing Scheme

A. Similarity Measures for Index Codes

Although most data collection protocols impose strict constraints on the data acquisition process, noise in the input images can significantly impact the match scores and, consequently, the index codes. The association between two index codes can be measured by their correlation. Index codes belonging to the same identity are expected to have a strong positive correlation. Index codes belonging to different identities are expected to be uncorrelated. We used the Pearson product-moment correlation coefficient

$$\rho(S_x, S_y) = \frac{\mathrm{Cov}(\mathcal{S}_x, \mathcal{S}_y)}{[\mathrm{Var}(\mathcal{S}_x)\mathrm{Var}(\mathcal{S}_y)]^{1/2}}. \quad (3)$$

Index codes can also be viewed as points in a Euclidean space, and the similarity between them can be measured by their spatial proximity. Two examples of such measures are the Euclidean distance

$$l_2(S_x, S_y) = \left(\sum_{i=1}^{n} (S_{x_i} - S_{y_i})^2 \right)^{1/2} \quad (4)$$

and the cosine similarity

$$\cos(S_x, S_y) = \frac{S_x \cdot S_y}{(S_x \cdot S_x)^{1/2}(S_y \cdot S_y)^{1/2}} \quad (5)$$

where "·" is the dot product.

B. Dimensionality of the Index Codes

While using a larger number of reference images can improve indexing performance it also increases the computational requirements of the method (as discussed in Section III-B). Furthermore, increasing the number of reference images beyond a certain number is not beneficial because the improvement in accuracy will be insignificant compared to the increased overhead. Generally, as more images are included in the reference set, the variability among them decreases (unless the biometric template has infinite capacity). Therefore, this number should be chosen empirically according to the desired accuracy and speedup. We provide guidelines for choosing this number in Section VII.

C. Selecting Reference Images

Reference images can be selected from the database itself. They can also be synthetically generated images. While the entire database can be viewed as a candidate pool for selecting reference images, practical considerations dictate the use of a small random subset of images for this purpose. A greater degree of diversity among the reference images increases the probability that the index codes of different subjects will be unique and well-spread in space. We consider three different selection rules for ensuring good diversity.

- First, the *max-variation* rule selects reference images with the largest variances of impostor match scores (match scores against images of different identities).

Algorithm for selecting n reference images (*max-variation* rule):

Let $\boldsymbol{F} = \{f_1, f_2, \ldots, f_Q\}$ be the candidate pool of reference images, and $s(x, y)$ be the match score between images x and y.

1) For each image f_i, $i = 1 \ldots Q$, compute $v_i = \mathrm{Var}\{s(f_i, f_j)\}_{j=1, j\neq i}^{Q}$.
2) Sort the images in descending order of their v_i values.
3) Use the top n images as reference images.

- Second, the *max-mean* rule selects images whose impostor match scores have a large mean value (the Var operator in the above algorithm is replaced by the sample mean operator). The rationale of this rule is to avoid selecting reference images resulting in sparse index codes (i.e., index codes that contain many zeros).
- Third, the *min-correlation* rule selects an optimal set of reference images by 1) starting with the entire candidate pool, 2) removing the image whose average correlation to other images in the set is the highest, and 3) repeating this process until the desired number of reference images is obtained. The first two selection rules do not account for similarities among the reference images. Thus, some of the selected reference images may have very similar characteristics. While this phenomenon does not necessarily reduce the hit rate, it results in redundant entries within each index code. The min-correlation rule attempts to overcome this drawback by reducing the pairwise correlation among the impostor match scores of the reference images.

VI. EXPERIMENTS

A. Databases and Matchers

There are very few publicly available multimodal biometric databases. Examples include WVU [34], BioSecure [35], XM2VTS [36], MBGC [37], and BANCA [38]. However, these databases have small numbers of subjects (fewer than 300 subjects each) and, therefore, cannot be used to evaluate our indexing approach in a reliable manner. Therefore, we assembled a chimeric multimodal dataset using the FERET face database [39] and the WVU fingerprint database [34]. There are 1195 subjects with frontal face images in the FERET database. We used only 1010 of these subjects because the images of the remaining 185 subjects could not be processed by the face matcher used in this work. Sample images are shown in Fig. 6.

The WVU fingerprint database contains images of 4 different fingers (left index, left thumb, right index, right thumb) from 270 subjects. We treated the individual fingers as independent "subjects," resulting in a total of 1080 subjects. However, because the matcher could not process the images of 210 subjects, a total of 870 subjects were used in the experiments. Two images per subject were used from the WVU database—one for enrolling the subject into the database and the other one as a probe image. Sample images from the WVU database are shown in Fig. 7. Virtual identities were created by randomly pairing subjects from these two databases.

(a) (b)

Fig. 6. Sample images from (a) the FERET and (b) the FRGC databases. Faces with smiling expressions were enrolled in the database, while those with neutral expressions were used as probes for evaluating performance.

Fig. 7. Sample images from the WVU fingerprint database. Images from different fingers of the same individual were treated as different subjects.

In addition, the FRGC [40] face database (Experiment 4) was used in the face indexing experiments in order to demonstrate the robustness of the proposed indexing scheme to varying image quality. A total of 568 subjects were available in this dataset. Both face databases that we used contain variations in facial expression. Examples are shown in Fig. 6. In the experiments below, the face images in the gallery had smiling expressions while the probe images had neutral expressions.

Two face matchers (VeriLook 2.1 by Neurotechnology and FaceIt 6.1.1 by Identix) and one fingerprint matcher (VeriFinger 4.1 by Neurotechnology) were used in the experiments. For both matchers from Neurotechnology, the matching threshold was set to its minimum value to avoid quantization of the match scores.

B. Evaluation of Indexing Performance

The performance of indexing algorithms is commonly evaluated using the hit rate and penetration rate. The hit rate is the percentage of probes for which the corresponding gallery image with the correct identity is retrieved by the indexing mechanism

$$\text{Hit rate} = \frac{N_h}{N} \tag{6}$$

where N_h is the number of probes for which the correct identity is present in the retrieved candidate list and N is the total number of probes for which indexing was attempted. The penetration rate denotes the average percentage of gallery entries that have to be retrieved based on the indexing scheme

$$\text{Penetration rate} = \frac{1}{N}\sum_{i=1}^{N}\frac{L_i}{M} \tag{7}$$

where L_i is the number of identities in the candidate list of the ith probe image and M is the number of identities in the database. In our experiments, $N = M$. An effective indexing scheme will have a high hit rate and a low penetration rate.

TABLE IV
EER AND d' WERE CALCULATED FOR THE DISTRIBUTION OF IMPOSTOR AND GENUINE DISTANCES AMONG INDEX CODES. LARGE d' VALUES INDICATE BETTER SEPARATION BETWEEN THE IMPOSTOR AND GENUINE DISTRIBUTION. SMALLER EER VALUES GENERALLY CORRESPOND TO SMALLER AREAS OF OVERLAP BETWEEN THE TWO DISTRIBUTIONS

	Pearson's ρ		cos similarity		l_2 distance	
	d'	EER	d'	EER	d'	EER
FERET	**1.96**	**0.076**	1.86	0.084	1.49	0.136
WVU	**2.10**	**0.079**	1.73	0.113	1.44	0.149

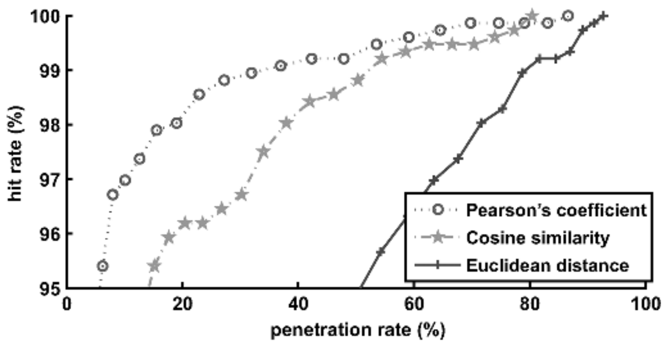

Fig. 8. Indexing performance of three distance measures on the FERET database. Penetration rates are the mean values obtained using cross-validation by random subsampling. One hundred splits, each consisting of 800 randomly selected images, were used.

C. Parameters

1) Similarity Measures: The effect of the distance measure discussed in Section V-A was studied by evaluating the overlap between the distributions of genuine (same identities) and impostor (different identities) distances among index codes. The d' statistic

$$d'(\text{impostor}, \text{genuine}) = \frac{|\mu_{\text{impostor}} - \mu_{\text{genuine}}|}{\left(\sigma^2_{\text{impostor}} + \sigma^2_{\text{genuine}}\right)^{1/2}}$$

and the equal error rate (EER), calculated for these distributions on the FERET database are reported in Table IV. The corresponding indexing performance is shown in Fig. 8. Pearson's correlation coefficient was the distance measure that resulted in the best performance for both modalities and was used in all subsequent indexing experiments.

2) Selection Rules for Reference Images: The three selection rules for reference images (discussed in Section V-C), were compared against the baseline scheme of random selection. Cross-validation by random subsampling was used to account for variations in the pool of images from which reference images are selected. More precisely, 100 random subsets each consisting of 800 images were used to evaluate the performance of each selection rule. Table V shows the mean EER and d' statistic of the impostor and the genuine distributions. The entries in Table V (a) and Table V (b) are sorted by increasing EER. The max-mean rule was the only rule consistently placed in the top two rows. Therefore, the reference images in the following experiments were selected by applying this rule on the entire database. The identities corresponding to the reference

TABLE V
PERFORMANCE OF THREE DIFFERENT RULES FOR SELECTING REFERENCE IMAGES. THE ENTRIES IN (a) AND (b) ARE SORTED BY INCREASING EER. THE MAX-MEAN RULE IS CONSISTENTLY PLACED IN THE TOP TWO ROWS

	EER	d'
random	0.077	2.16
max-mean	0.079	2.08
max-variation	0.088	2.03
min-correlation	0.089	2.07

(a)

	EER	d'
max-mean	0.059	2.06
max-variation	0.060	2.07
random	0.068	2.00
min-correlation	0.072	1.95

(b)

TABLE VI
EER AND d' CALCULATED FOR THE GENUINE AND IMPOSTOR DISTRIBUTIONS OF CORRELATION COEFFICIENTS AMONG INDEX CODES

	$n = 50$	$n = 100$	$n = 150$	$n = 250$
EER	0.16	0.10	0.08	**0.05**
d'	1.43	1.81	1.98	**2.18**

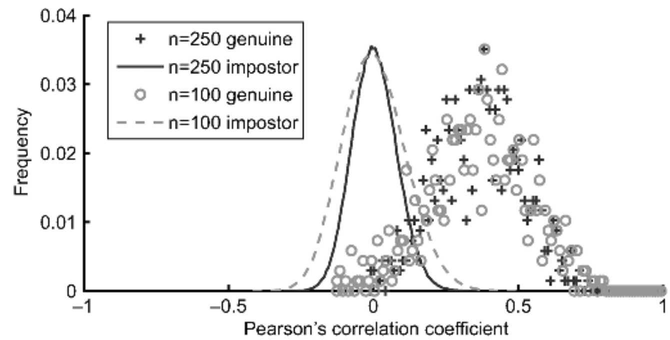

Fig. 9. Genuine and impostor distributions of correlation coefficients between index codes. Increasing the dimensionality n of the index codes results in a smaller overlap between the genuine and impostor distributions.

images were removed from the database when evaluating the performance of indexing.

3) Number of Reference Images: The effect of the number of reference images was evaluated using a fixed probe set from the FERET database. Four different index codes were generated using four different values of n. The resulting EER and d' values are shown in Table VI. The change in the genuine and impostor distributions of correlation coefficients for two values of n can be seen in Fig. 9. In general, larger values[1] of n result in smaller overlaps between the impostor and genuine distributions, leading to better indexing performance.

VII. RESULTS

Unless otherwise specified, the results in this section were obtained by performing 10-fold cross-validation repeated 10 times, which gives 100 estimates of the penetration rate for a given hit rate. The mean value and the 99th percentile from the distribution of these estimates were used to assess the performance of our indexing approach.

We used 250 reference images ($n = 250$) selected by the *max-mean* selection rule. Thus, 760 identities (i.e., $1010 - 250 = 760$) from the FERET database, 318 identities (i.e., $568 - 250 = 318$) from the FRGC database, and 620 identities (i.e., $870 - 250 = 620$) from the WVU database

[1]The effect of curse-of-dimensionality has not been investigated in this study.

Fig. 10. Top 16 reference images from the FERET database selected by the *max-mean* rule.

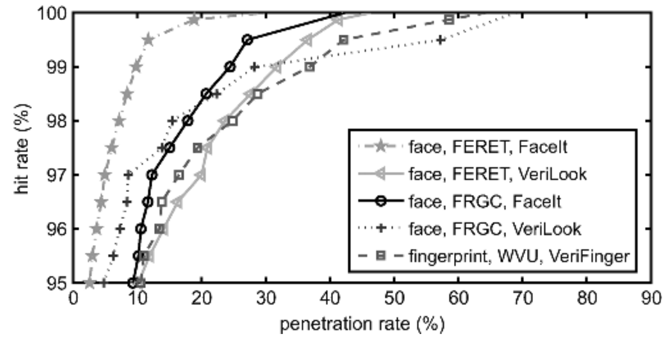

Fig. 11. Indexing performance of single modalities using different databases and matchers.

TABLE VII
PENETRATION RATES (%) FOR THE FACE INDEXING METHOD OF PERRONNIN AND DUGELAY [27] AND THE PROPOSED METHOD ON THE FERET DATABASE. THE 100TH CROSS-VALIDATION PERCENTILE OF THE PENETRATION RATE IS SHOWN IN PARENTHESES

Hit rate (%)	**100**	**99**	**98**	**95**	**94**	**90**
Ref. [27]	*	*	*	20	10	6
proposed (FI)	**30 (31)**	**10 (11)**	**7 (8)**	**3 (3)**	**2 (3)**	**1 (1)**
proposed (VL)	46 (47)	32 (32)	23 (24)	10 (12)	8 (9)	4 (4)
reference images from the FRGC database						
proposed (VL)	86 (87)	39 (41)	28 (30)	13 (15)	10 (11)	4 (5)

were used in the evaluation. Results for each database were obtained by using reference images from the same database. For the face modality, the reference set was determined by using the scores produced by the VeriLook matcher and the same set was used when evaluating the performance using the FaceIt matcher. Fig. 10 shows the top 16 reference images from the FERET database. For brevity we will use the abbreviations VL and FI, for the VeriLook and the FaceIt matcher, respectively.

A. Unimodal Databases

The performance of the proposed indexing method on the two face databases and the fingerprint database is shown in Fig. 11. Performance was better for the face modality than for the fingerprint modality. The main reason for this result is probably the large number of zero-valued match scores in the fingerprint modality. The set of fingerprint scores generated by matching an image in the WVU database against other images in the database contains 27% zero-valued scores, on average. The results presented in Fig. 11 indicate that the FaceIt matcher outperformed the VeriLook matcher. Furthermore, the penetration rates on the FERET database are generally lower than those on the FRGC database. The effect of using different matchers is discussed further in Section VII-B.

We compared the performance of the proposed method against the indexing technique proposed by Perronnin and Dugelay [27] on the FERET database. As shown in Table VII, our technique achieved lower penetration rates for both face matchers. Perronnin and Dugelay [27] used the frontal images of 500 subjects from the FERET database. Although this set of images may not exactly correspond to the set of images we used, there is likely to be a substantial overlap between them. Furthermore, we present the results (of our technique) from the 100th cross-validation percentile in order to demonstrate the low variance in penetration rates across different evaluation sets. The difference between the average and the worst case performance is very small. Therefore, similar performance can be expected on other image subsets from the same database.

The results in the last row of Table VII were calculated using reference images from the FRGC database. This allowed us to have 1142 identities for evaluation, which represents almost the entire set of identities with frontal-view images in the FERET database. The evaluation set consisted of the 760 identities in the probe set, the 250 identities used as reference images and an additional 132 identities for which the match scores were extracted using the VeriLook matcher after disabling its image-quality checker.

The penetration rates in the fingerprint modality were slightly higher compared to the face modality. However, even in the case of fingerprints, at a 98% hit rate the penetration rate was 25%, which shows the efficacy of the proposed technique even without modality-specific tuning.

B. Choice of Matcher

The choice of face matcher had a strong effect on the performance of indexing. The FaceIt (FI) matcher resulted in consistently lower penetration rates compared to the VeriLook (VL) matcher, which can be seen in Fig. 12. The FaceIt matcher also has better recognition performance, which might be the reason for its better indexing performance. Matchers having lower verification accuracies are likely to have lower indexing performances. For a subset of 466 subjects from the FERET database, the FaceIt matcher resulted in an EER of 0.001, whereas the VeriLook matcher resulted in an EER of 0.0084. At the same time, the penetration rates at a 99% hit rate were 10% and 32%, respectively, for the two matchers. The same trend is observed on the FRGC database. The FaceIt matcher had lower EER and better indexing performance. Matchers that are used in biometric identification systems are typically optimized for the conditions under which they are operating, e.g., outdoor/indoor, lighting variations, etc. Therefore, the proposed indexing

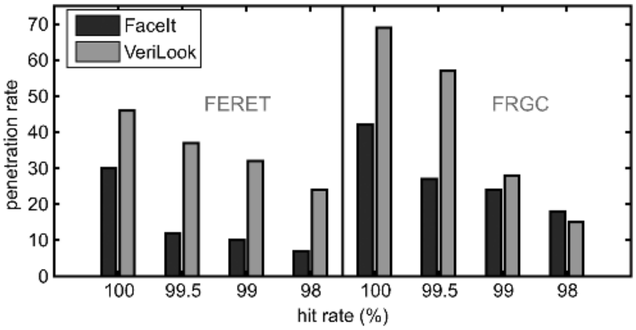

Fig. 12. Penetration rates for the two face matchers on the two databases. Results for the FERET database are shown on the left and those for the FRGC database are shown on the right.

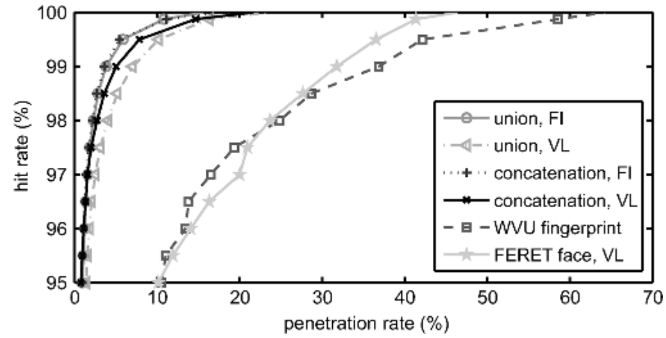

Fig. 14. Improvement in performance after fusing the fingerprint and the face modalities.

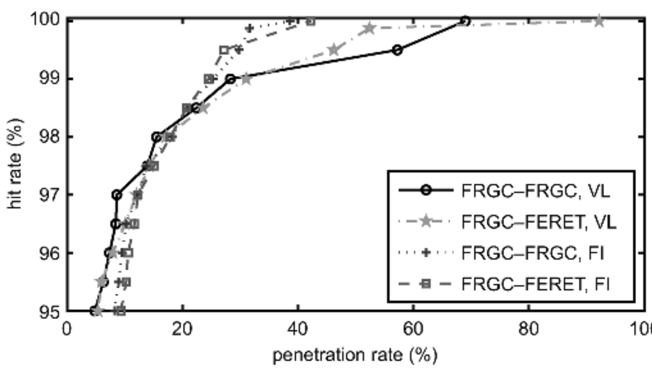

Fig. 13. Indexing performance when reference images and evaluation images belong to different face databases. In the legend, the name on the left indicates the database used for evaluation and the name on the right indicates the database used to select the reference images.

method does not have to be tuned for specific imaging conditions.

C. Reference Images From a Different Database

Changes in illumination conditions and pose of the head are common problems in face recognition. Similarly, fingerprint recognition has larger error rates when the enrolled image and the probe are captured by different sensors. Thus, it is logical to select the reference images from the database of enrolled images. However, in certain scenarios, e.g., when the enrolled images come from diverse sources, it might be better to use reference images that were collected under constrained imaging conditions and exhibiting good quality. To test the effect of using reference images that have different image characteristics from those of the images in the evaluation database, we used the reference set from the FERET database to index the FRGC database. The results from this experiment are shown in Fig. 13. We used a fixed probe set and enrolled image set, and performed indexing by first using the reference set from the FRGC database (base case) and then by using the reference set from the FERET database (external images). Interestingly, for both face matchers, the performance of indexing when using external images was not significantly different from the base case, except for the most challenging 1% of the enrolled identities (i.e., to achieve a hit rate greater than 99%).

D. Bimodal Databases

Poh and Bengio [41] stated that, in certain cases, identification results obtained on chimeric multimodal databases may not be representative of the true identification performance. To account for these situations, the performance of multimodal indexing was evaluated by extensive cross-validation. Thus, the chance of underestimating the true (unknown) penetration rate was reduced. In this experiment, the face and fingerprint images from the FERET and WVU databases, respectively, were paired in an exhaustive manner. Each of the 760 identities in the FERET database was coupled with each of the 620 identities from the WVU database, resulting in 471 200 bimodal identities. These identities were split into 760 bimodal datasets, each having a size of 620. Every single bimodal dataset included all identities from the WVU database and 620 unique identities from the FERET database. Thus, we ensured that every possible combination of face and fingerprint images was used as a bimodal identity. This allowed us to evaluate the variance of the estimated penetration rates and avoid their underestimation due to the chimeric nature of the database.

The results of indexing bimodal databases are shown in Fig. 14. Although, the mean of the penetration rates obtained for the concatenation and union fusion rules were similar, the union fusion rule resulted in lower variance. The mean and the 99th percentile of the distribution of penetration rates are given in Table VIII. The penetration values of the 99th percentile at a 100% hit rate for the union fusion were 33% and 28%, respectively, for the FaceIt and the VeriLook matchers, whereas for the concatenation fusion these values were 54% and 55%, respectively. The results shown in Table VIII indicate that fusion improved the performance of indexing. For example, at a hit rate of 99%, the union fusion rule resulted in a penetration rate of 4%, compared to 37% for fingerprints and 10% for faces (FaceIt).

Fig. 15 shows that the distributions of the correlation coefficients are different for different modalities. Therefore, the decision threshold T^i has to be selected separately for each modality. In our fusion experiments, thresholds were chosen empirically to be τ standard deviations from the mean of the impostor distributions of correlation coefficients, where τ had the same value for both modalities. The mean values were estimated from the enrolled images. This is equivalent to performing a

TABLE VIII
PENETRATION RATES (%) AT MULTIPLE HIT RATES (%) FOR THE SINGLE MODALITIES AND TWO FUSION RULES. THE 99TH PERCENTILE FROM CROSS VALIDATION ARE SHOWN IN PARENTHESIS

hit rate (%)	100	99.5	99	98.5	98
WVU	64	42	37	29	25
FERET VL	46	37	32	28	24
FERET FI	30	12	10	8	7
concat. (WVU+VL)	22 (55)	8 (19)	5 (10)	4 (7)	3 (6)
concat. (WVU+FI)	18 (54)	5 (16)	4 (8)	3 (6)	2 (4)
union (WVU+VL)	23 (28)	10 (18)	7 (11)	5 (9)	4 (7)
union (WVU+FI)	**16** (33)	**6** (12)	**4** (9)	**3** (7)	**2** (5)

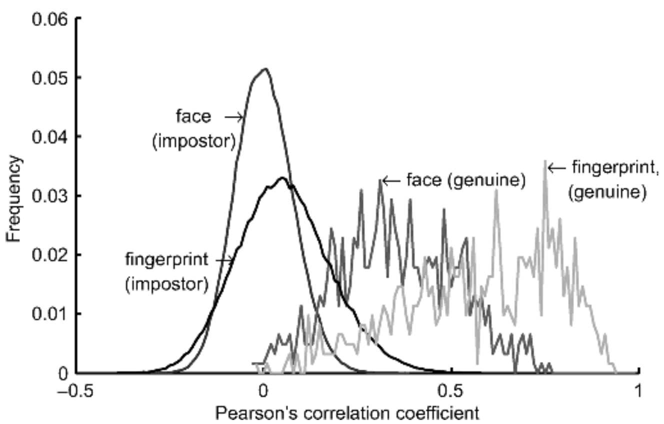

Fig. 15. Genuine and impostor distributions of the correlation between pairs of index codes.

z-score normalization on the impostor distributions of correlation coefficients and using the same threshold for both modalities.

Similarly, before concatenating the index codes, the match scores constituting the two index codes had to be normalized because the two matchers output scores in different ranges and/or different distributions.

E. Effect of the Size of the Database

A simulation study was conducted to assess the performance of the proposed system on large databases (i.e., containing thousands of identities). Using the FERET database, a large number of index codes of dimension $n = 250$ were created by modeling the impostor match scores of the face matcher. The new index codes were generated by randomly sampling the set of match scores associated with the reference images. If ξ_i is the set of match scores for reference image i and $m(\xi_i)$ is a match score sampled from ξ_i, then a new index code was synthesized as $\mathcal{C} = \{m(\xi_1), m(\xi_2), \ldots, m(\xi_n)\}$. These sets were sampled with replacement to generate 20 000 synthetic index codes.

The simulated large database consisted of these 20 000 synthetic index codes and the 760 gallery index codes from the FERET database. The performance of our indexing scheme was evaluated on this large database using the 760 probe index codes from the FERET database. Indexing performance on this synthetically created database (20 760 identities) relative to the actual database of 760 identities is shown in Fig. 16. The performance using synthetic index codes is similar to the performance

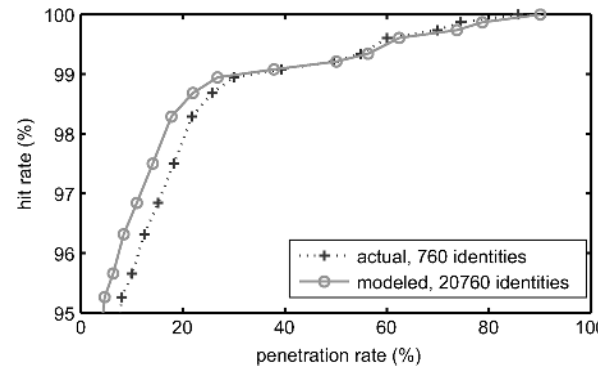

Fig. 16. Indexing performance using real index codes and synthetically generated index codes based on 250 reference images.

on actual identities. This suggests that the impostor distributions shown in Fig. 15 may not change substantially for larger databases. Therefore, the number of reference images could potentially be determined based on the impostor distribution of correlations among the index codes of a small set of images.

An additional experiment was performed in which the set of impostor match scores corresponding to each reference image was modeled using exponential distributions. New index codes were generated by sampling from these parametric distributions. Each element in a generated index code was sampled from the corresponding parametric distribution. The indexing results based on this generated data were almost identical to those shown in Fig. 16. This suggests that the bootstrapping method described in the previous paragraph is appropriate for generating synthetic index codes for evaluation purposes.

F. Computational Time

A nonoptimized implementation in Java JDK 5.0 computes the Pearson correlation coefficient between two index codes in an average of 0.0072 μs. The average matching rate, as reported by the VeriLook matcher, is 240 000 faces per second on the FERET database, which is about 4.2 μs for one matching operation. This time is computed based on an optimized C++ implementation that uses all 4 cores of the processor and does not include the time taken for storage and retrieval of the templates. The actual response time of the matcher, in our experiments, was observed to be much slower. We used the right-hand side of inequality (1) to determine the speedup that can be achieved by the proposed technique on databases of different sizes using the VeriLook matcher. Results from this calculation are shown in Table IX.

VIII. DISCUSSION AND FUTURE WORK

We presented a method for indexing biometric databases for efficient identity retrieval. The proposed technique is not modality-specific. Therefore, it can easily be incorporated into existing biometric systems. The biometric matcher that is inherent to the system can be used for generating index codes. Furthermore, the application of our approach to multibiometric databases is straightforward. Using the proposed indexing technique on a chimeric multimodal database resulted in a reduction of the search space by an average of 84% at a 100% hit rate. The use of reference images that had different sizes,

TABLE IX
FRACTIONAL REDUCTION IN COMPUTATIONAL TIME AS A RESULT OF INDEXING USING THE VERILOOK MATCHER

Size of the database	Penetration rate (%) 50	40	30	20	10	5
1,000	.75	.65	.55	.45	.35	.30
5,000	.55	.45	.35	.25	.15	.10
10,000	.527	.427	.327	.227	.127	.077
50,000	.507	.407	.307	.207	.107	.057

image resolutions, and color depths, compared to the images in the database, did not change the performance of the proposed indexing method substantially. In this case, penetration rates were higher only for hit rates above 99%. Results from indexing a chimeric bimodal database indicated that fusion by union of candidate lists had better performance than fusion by concatenation of index codes. Z-score normalization played an important role in optimizing the performance of the two fusion techniques. The main factor for the amount of speedup during identification was the penetration rate of the indexing.

Several characteristics of the proposed method can be explored to further improve its performance. First, quantization of the match scores may improve indexing performance. Second, a representative set of reference images can be selected based on properties of the feature space (as opposed to the score space). For example, reference images can be selected from the convex hull of the feature space in order to ensure sufficient diversity across index codes. However, this approach may not be appropriate if the feature space is not Euclidean (or does not conform to Riemannian geometry). Third, multiple matchers may be used to generate the index code for each modality. Overall, the proposed method is easy to implement and deploy, can be applied to various biometric databases, and can significantly improve the response time of large-scale unimodal as well as multibiometric systems.

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