

A Hybrid Approach to Multimodal Biometric Recognition Based on Feature-level Fusion of Face, Two Irises, and Both Thumbprints

Abstract

Background: The most significant motivations for designing multi-biometric systems are high-accuracy recognition, high-security assurances as well as overcoming the limitations like non-universality, noisy sensor data, and large intra-user variations. Therefore, choosing data for fusion is of high significance for the design of a multimodal biometric system. The feature vectors contain richer information than the scores, decisions and even raw data, thereby making feature-level fusion more effective than other levels. **Method:** In the proposed method, kernel is used for fusion in feature space. First, the face features are extracted using kernel-based methods, the features of both right and left irises are extracted using Hough Transform and Daugman algorithm methods, and the features of both thumb prints are extracted using the Gabor filter bank. Second, after normalization operations, we use kernel methods to map the feature vectors to a kernel Hilbert space where non-linear relations are shown as linear for the purpose of compatibility of feature spaces. Then, dimensionality reduction algorithms are used to the fusion of the feature vectors extracted from fingerprints, irises and the face. since the proposed system uses face, both right and left irises and right and left thumbprints, it is hybrid multi-biometric system. We carried out the tests on seven databases. **Results:** Our results show that the hybrid multimodal template, while being secure against spoof attacks and making the system robust, can use the dimensionality of only 15 features to increase the accuracy of a hybrid multimodal biometric system to 100%, which shows a significant improvement compared with uni-biometric and other multimodal systems. **Conclusion:** The proposed method can be used to search large databases. Consequently, a large database of a secure multimodal template could be correctly differentiated based on the corresponding class of a test sample without any consistency error.

Keywords: Feature-level fusion, hybrid, kernel, multimodal biometric

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Introduction

The biometric systems relying on single biometric modality have the drawback of considerable limitations owing to biometric traits, poor data quality, and noise. Multi-biometric systems use fusion to integrate multiple biometric sources so that the authentication accuracy is improved.^[1] There could be five rationally perceivable scenarios provisioning multiple biometric information sources. According to various available evidence sources, multi-biometric systems can be categorized into five multi-sensor, multi-algorithm, multi-instance, multi-sample, and multimodal system scenarios, where in the first four, several pieces of evidence can be drawn from only one single specific biometric trait (i.e., iris or fingerprint).

This is while, for the 5th scenario (called as the multimodal biometric system), several biometric traits (i.e., iris and fingerprint) can be considered. Another possibility for a multi-biometric system is to use a combined set of scenarios picked from the above said five scenarios (typically known as hybrid multi-biometric systems). Moreover, to improve the user authentication complexity and security, a greater number of traits are combined together.^[2] Hence, the implementation of multimodal biometric systems is recommended to address the aforesaid problems. Multimodal biometrics due to its enhanced reliability, applicability, and security, has evolved into a biometric recognition development orientation for many researchers.^[3] Biometric data fusion may take place at four levels. If it happens at the sensor level,^[4] raw data will be combined. This type of fusion is illogical for

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designing a multimodal system; however, it can be helpful for increasing the efficiency of a uni-biometric system. Feature-level fusion combines the feature vectors extracted from various biometrics of the same class. Furthermore, the scores achieved from various classifications may be combined at the score level^[5] in case each classifier pertains to a single biometric. Owing to its simplicity and low-cost processing, this method is the most popular technique of fusion utilized in designing a biometric multi-biometric system. Finally, decision-level fusion may occur through combining several decisions, each of which is the product of a uni-biometric system.^[6] Decision-level fusion is less efficient than even score-level fusion. Both the mentioned two levels rely on the unimodal biometrics recognition performance, when a limited space is to be improved. Feature level compared with the other three levels, is capable of detecting the most discriminative data from the original feature sets while removing the redundant information among the various feature sets.^[3] Therefore, it is clear that feature-level fusion method proves best for designing a multimodal system due to rich information at feature vectors [Figure 1].

Fusion of feature vectors could occur within a feature space for the purpose of transforming multiple feature vectors into a single vector so as for the final vector to have a higher detection power than the original vectors through the processes of “serial or parallel combination,”

“dimensionality reduction algorithms,” or “binary feature fusion.” This article suggests feature-level fusion of five biometric modalities pertaining to the face, right thumb and left thumb fingerprints, and both right and left irises in the dimensionality reduction process in order to achieve a robust and secure biometric template for multimodal recognition system. First, face feature vectors are extracted by Kernel Linear Discriminant Analysis (KLDA), fingerprint features are extracted using Gabor filter bank, and irises features are extracted by Hough transform and Daugman algorithm. Then, using normalization operations, the kernel methods are used for the purpose of compatibility between the three feature spaces and creating distinction between linear and nonlinear relations. In doing so, along with dimensionality reduction, the feature vectors of thumbprints, irises, and the face are combined through mapping on the kernel Hilbert space.

Material and Method

The block diagram of hybrid multimodal biometric system, comprising the three main modules of feature extraction, feature fusion, and classification, is demonstrated in Figure 2. The modules are explained in subsections.

Feature extraction module

The module for feature extraction extracts the best features for each of face, iris, and fingerprint biometrics separately and maps the system from image space to feature space.

Face feature extraction

As Figure 3 shows, to extract face features, in case the images have any other background than the face, first face detection algorithms are used to segregate the face from the background image. Then, face features are identified through using the algorithms introduced for face recognition, such as principal component analysis (PCA),^[7] linear discriminant analysis (LDA),^[8] locality preserving projections (LPPs)^[2] and local binary patterns,^[1] discrete

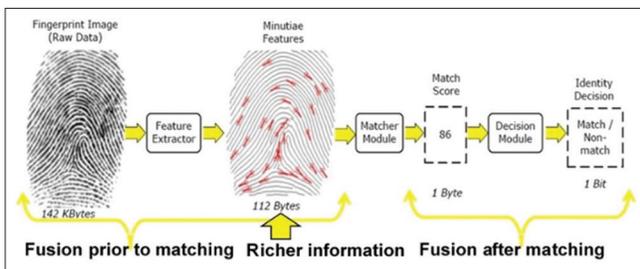


Figure 1: Different levels of fusion in multi-biometric

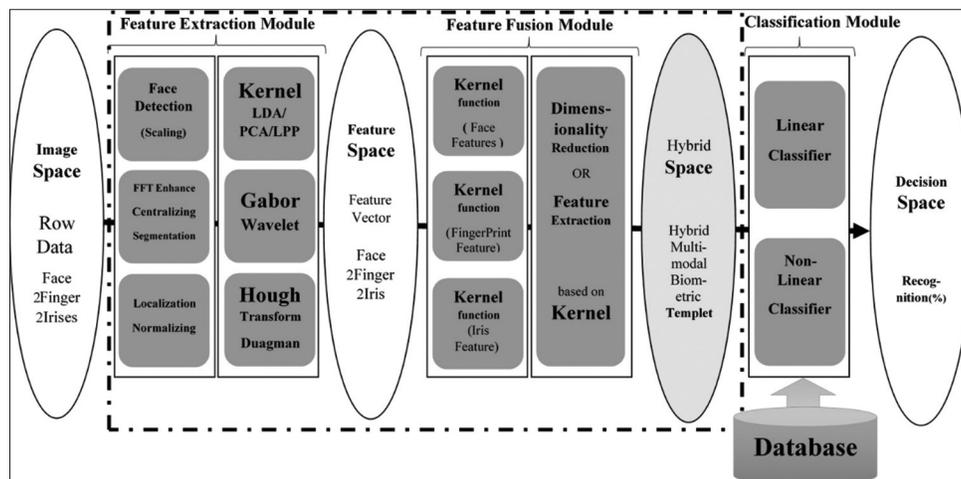


Figure 2: The hybrid multimodal biometric system diagram block

cosine transform^[9] and single value decomposition,^[10] canonical correlation analysis (CCA)^[11] and discriminant correlation analysis,^[12] neural networks (NNs), and deep learning.^[13]

Face recognition has wide applicability, as an important and interesting topic of computer vision domain. The application can cover a wide range from surveillance and human-computer interface to access control and augmented reality. Although, it is still a problematic challenge both due to intrinsic and extrinsic appearance changes (e.g., aging and expression variations, occlusion, pose, and

illumination variations).^[14] Therefore, face recognition issue often is considered nonlinear mostly owing to its complexity, number and small-scale prototypes of images as well as the associated complexities. Given that the kernel techniques may effectively register nonlinear similarities among the samples, face recognition methods based on kernel have been introduced to develop linear algorithms, in which corresponding kernel functions are utilized to map the samples implicitly on a new feature space with higher dimensionalities. The kernel function definition would be $k(x, y) = \langle Q(x), Q(y) \rangle$ where $Q: R^n \rightarrow H$ denotes nonlinear mapping from the original space to a kernel Hilbert space and $\langle Q(x), Q(y) \rangle$ denotes the dot product of the two data vectors $Q(x)$ and $Q(y)$. Therefore, kernel function calculations may be compared with the dot product of two pieces of data in the kernel Hilbert space corresponding to that kernel. This is an important property of kernel functions resulting in the introduction of kernel trick.^[15]

To find the best kernel function that can calculate the principal component or linear discriminant in a space by high-order correlations of the input pixels that create a face image, the input image is mapped into a higher-order feature space by using multiple kernels, and based on coding in Matlab, the kernel which responds better is going to be selected. The five kernel functions used for extracting face features as well as the kernel-based methods of dimensionality reduction, which are commonly used in many applications of kernel methods, can be represented as:



Figure 3: Face detector and extractor module

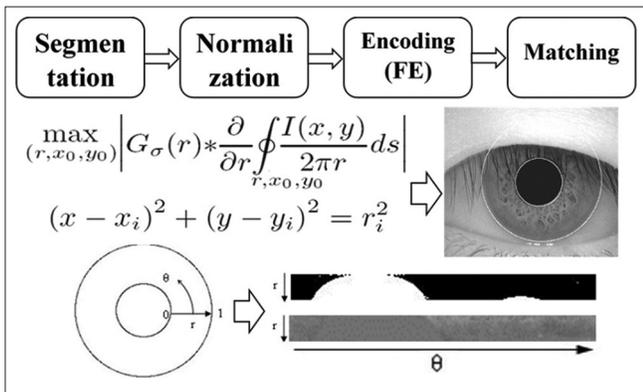


Figure 4: Iris segmentation and normalization

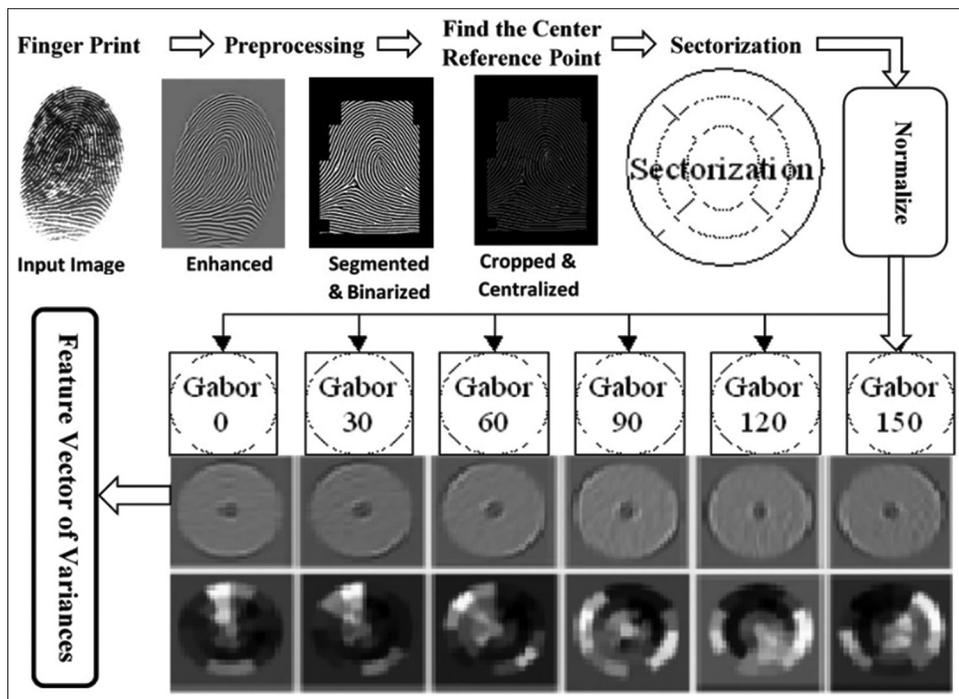


Figure 5: Fingerprint feature extraction steps and Gabor filter bank resulting

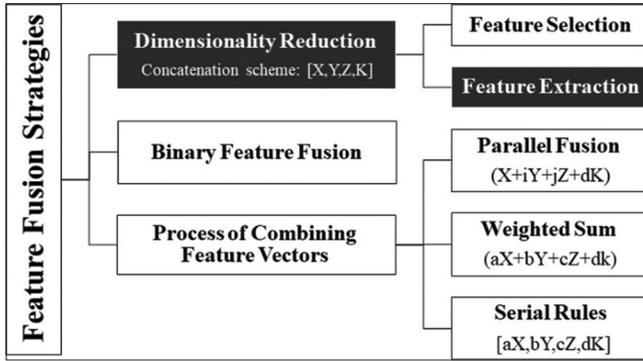


Figure 6: Fusion strategies for feature space

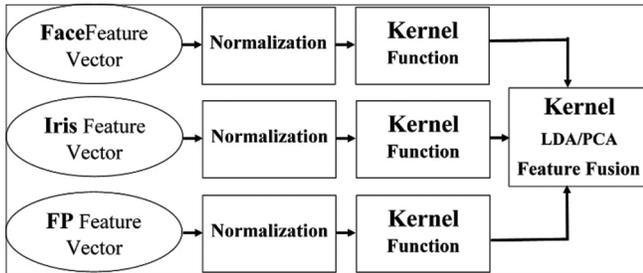


Figure 7: Fusion of features with dimensionality reduction algorithms based on kernel



Figure 8: Evaluated classifiers

Gaussian function: $k(x_i, x_j) = \exp\left(-\frac{|x_i - x_j|^2}{2\sigma^2}\right)$ (σ : Bandwidth parameter in Gaussian kernel) (1)

Polynomial function: $k(x_i, x_j) = (x_i, x_j)^d$ (d: Degree of polynomial function) (2)

PolyPlus function: $k(x_i, x_j) = (x_i(x_j + 1))^d$ (3)

Linear function: $k(x_i, x_j) = (x_i, x_j)$ (4)

Hamming function: $k(x_i, x_j) = 1 - \frac{1}{mN} \sum_1^m |x_i - x_j|$ (m: Number of pixels in the image) (5)

Iris feature extraction

Contrary to the existing challenges, iris recognition is attracting attention as an efficient biometric technology. The Daugman algorithm^[16] and Hough transform^[17] are used in extracting iris features. As Figure 4 shows, the algorithm for extracting iris features may be summarized in three steps:

1. The first and highly significant step in iris recognition is the iris boundaries' localization in the eye image
2. Afterward the establishment of the iris inner and outer boundaries, an invocation of geometric normalization scheme is made and then a rubber sheet model is used to transform the iris texture present in the annular region from Cartesian coordinates to pseudo polar coordinates. Images segregated from circles are normalized into rectangular block in an equally dimensional form
3. Although comparing the two irises can be made using the unwrapped iris (e.g., via correlation filters), generally a feature extraction procedure can be implemented for encoding the obtained textural content.

For the purpose of extracting the iris feature, the 1D Log-Gabor filter can be used on the normalized image for displaying the iris tissue information. The Log-Gabor filter, denoting the frequency response, can be represented as (6):

$$k(x_i, x_j) = \exp\left(\frac{-(\log\left(\frac{f}{f_0}\right))^2}{2(\log\left(\frac{\sigma}{f_0}\right))^2}\right) \quad (6)$$

where f_0 indicates the center frequency, and σ denotes the filter bandwidth.

The iris features are processed in a 9600-bit code and the upper and lower eyelashes in a 9600-bitmask.

Fingerprint feature extraction

Fingerprint recognition is primarily feature based (instead of being image based) and the used features would be having a physical interpretation. The fingerprint texture features are used as the fingerprint feature space. Such methods as the Gabor filter bank, minutiae Matching,^[18] short-time Fourier transform,^[19] and Gabor wavelet^[20] for fingerprint feature extraction. One common method of feature extraction is the Gabor filter bank that is illustrated in Figure 5.

After preprocessing (enhancement, binarization, and thinning steps) and improving the fingerprint image, the fingerprint feature extraction algorithm may be summarized in four major steps:

1. Determining the reference point and corresponding target area
2. Segmenting the target area around the reference point
3. Filtering the target area at six or eight different directions using the Gabor filter bank

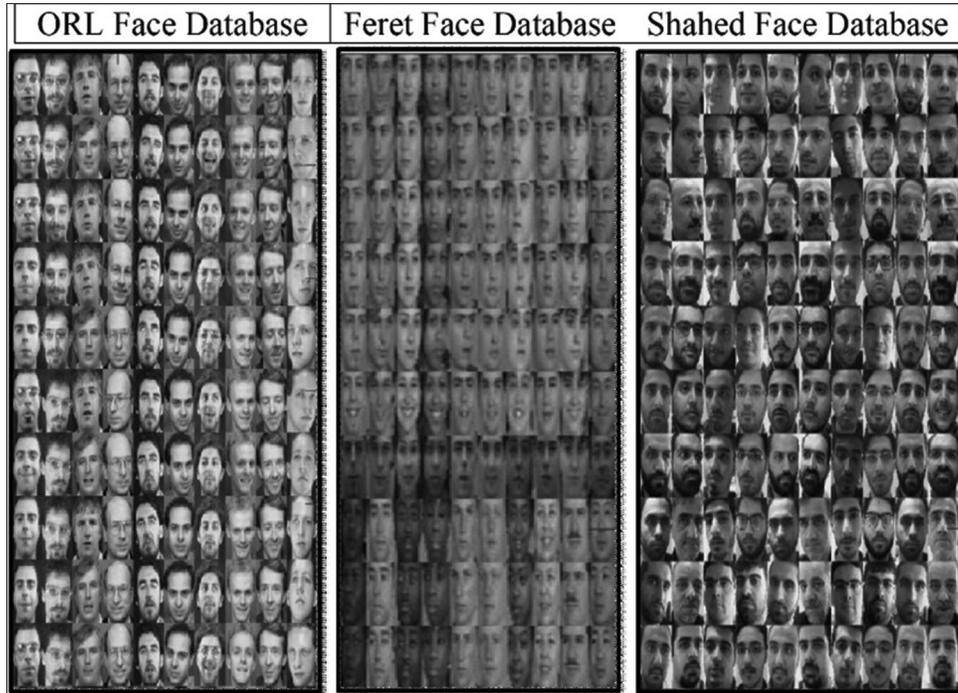


Figure 9: Image samples from ORL, FERET, and Shahed face databases (partial)

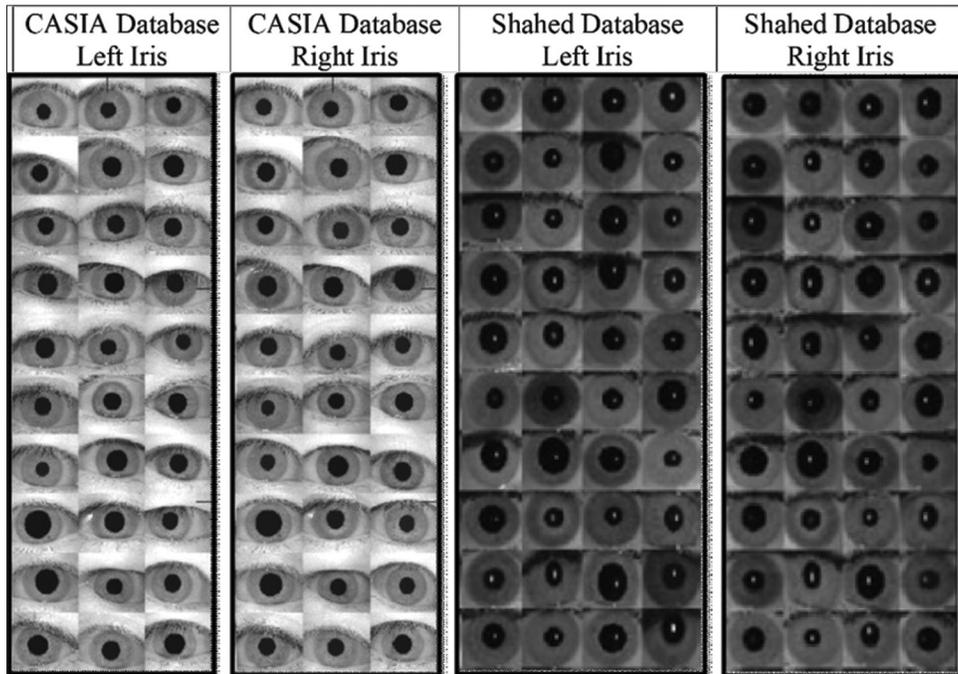


Figure 10: Image samples from CASIA and Shahed iris databases (partial)

- Calculating the absolute standard deviation of gray levels at each segment in order to generate a feature vector.^[21]

Feature fusion module

The feature space contains the richest data. It means that feature vectors are better both quantitatively and qualitatively than other levels in terms of information. Data fusion in

the feature space containing the main components and discriminants of raw data (image space) is important from two aspects: first, they can derive a combination of discriminant information from the original set of features; second, they can separately eliminate extraneous and repetitive information produced by correlation between the set of features in order to make the best decision in the shortest possible time. In other words, feature fusion would produce the best vector to

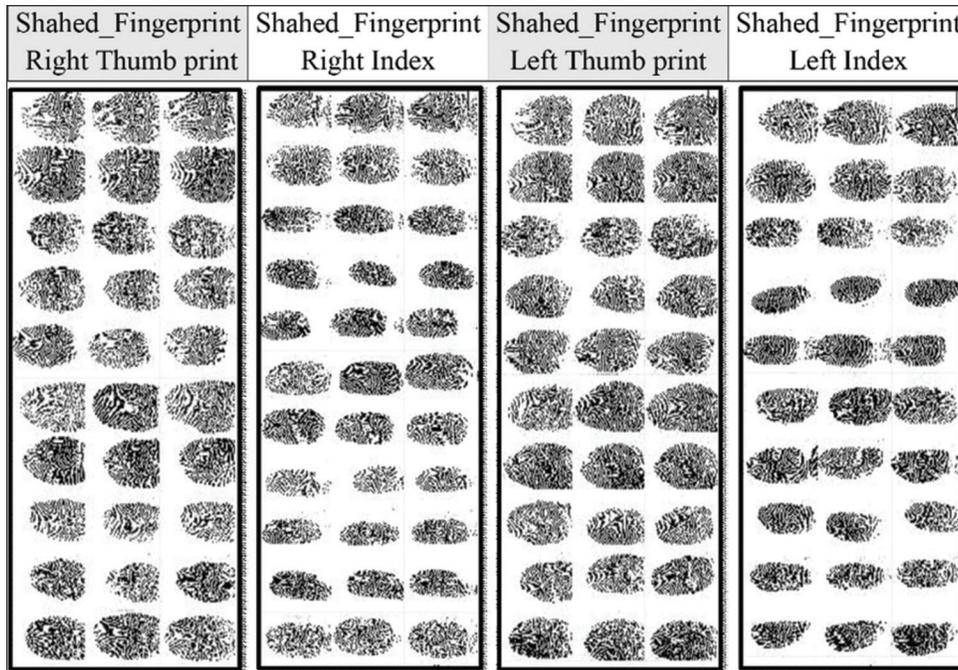


Figure 11: Image samples from Shahed thumb and index fingerprint databases (partial)

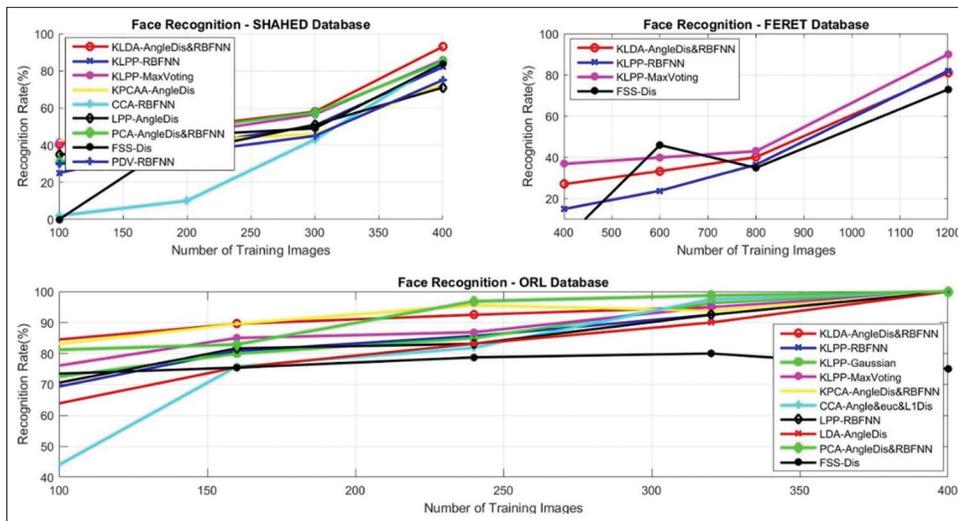


Figure 12: Results of face recognition by the uni-biometric system on ORL, FERET, and Shahed databases

create maximum distinction and have minimum dimensions for the system to make the best decision.^[6]

Figure 6 illustrates the strategy of vector fusion in the feature space. The feature space is based on the three processes of “serial or parallel combination^[1,3], “dimensionality reduction” methods including “feature extraction” and “feature selection”^[22-25] or binary feature fusion.^[22,26,27]

In this article, the features of right and left thumbprints, right and left irises, and the face are combined through the process of “dimensionality reduction.” As shown in Figure 7, feature space fusion would take place in three separate steps. Initially, we normalize the feature

vectors, i.e., the features not located in the same range are transferred to a similar range. We often see very extensive differences in the various ranges of feature vector values between the first, second, and third feature spaces. Therefore, normalization is necessary in all the three feature spaces before their fusion. If normalization is not carried out, the impact of one of space features will be dominant in the final result. In other words, feature vectors may have different distribution and variation ranges, which would impart them a significantly different impact after the fusion of the feature vector and the final result. Therefore, feature vectors must be normalized before fusion. The aim of normalization algorithms is often to change the mean and the variance of datasets to specific values. Using a

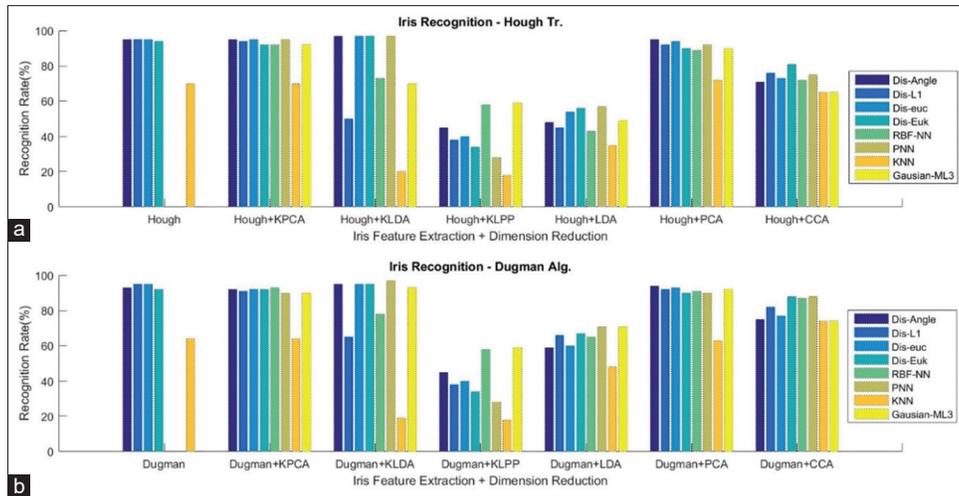


Figure 13: Comparing results of multi-instance iris recognition system, (a) Hough transform, (b) Daugman with dimensionality reduction algorithms

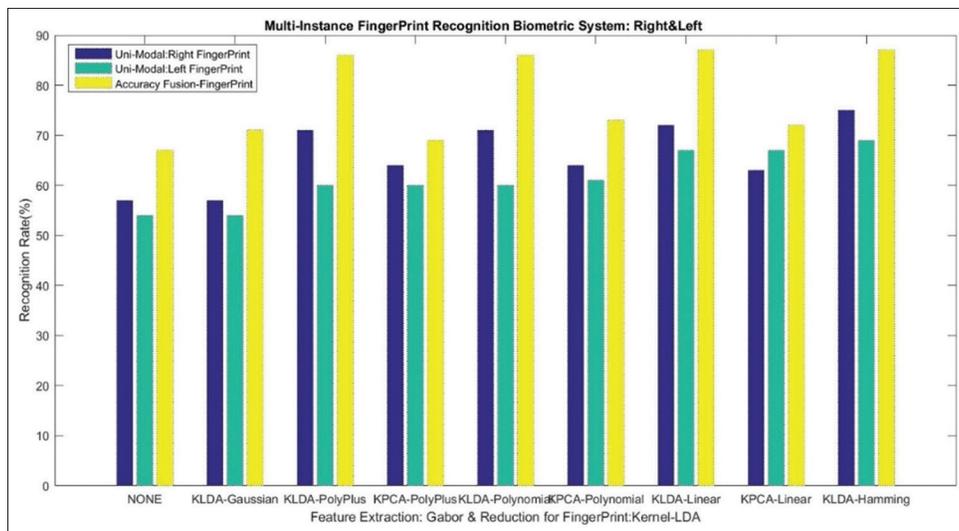


Figure 14: Comparing results of uni-biometric and multi-instance fingerprints recognition system with dimensionality reduction algorithms

single appropriate normalization method would also help fix the problem of outliers, which constitute one major reason for the education phase error. Such methods as min-max, median, and z-score are used for normalizing numeric datasets.

After normalization, kernel proper functions are applied separately on each of the feature spaces of the fingerprints, the irises, and the face in order to be transferred to the higher feature space of the kernel, where nonlinear relations are shown as linear. Then, in this space, by orthogonal linear transformation of PCA, the features are mapped on the new coordinate system so that the biggest variance of features is mapped on the 1th coordinate axis, the second-largest variance on the 2nd coordinate axis, and so on. That would help preserve the components from the main set with the most impact on variance to reduce dimensionality and help feature space fusion materialize. Real-world

recognition applications face non-linear issues due to big dimensions, original data noise, and correlation between variables, requiring kernel-based dimensionality reduction methods (choosing the appropriate kernel).^[28] There is often overlapping in the class distribution, and in most cases, as the number of classes increases, the recognition precision decreases. Therefore, on the one hand, using the appropriate kernel function in each feature space can lead to favorable separation between classes, and on the other, using LDA in the kernel Hilbert space can create a class structure. Therefore, the problems caused by the few number of samples and absence of supervisor will be resolved so that we will see better results from the fusion of the three sets of features. Using kernel non-LDA for the set of features in which class separation will be created means maximum correlation between the samples of each class while simultaneously the correlation between the samples from various classes is minimized. It is proven

in this method that using the inner product operator between the features in the original space, it would be possible to directly find the optimal answer to the kernel non-LDA without having to compute the kernel function for reach of original space features.

Classifier module

As explained in previous sections, first the features of face, iris, and fingerprint images are extracted. Next, afterward the normalization through mapping feature vectors in the kernel (Hilbert) space, PCA or discrimination (for creating class structure) is used to reduce dimensionality and store a multimodal template of biometrics representing each class in the database. Finally, the classifier module compares every time in the recognition phase the new biometric multimodal

template obtained from previous modules (extractor and feature fusion) with the combined modules previously stored in the database in the enrollment phase to determine its class based on further similarity (or shorter distance) between the new template and the stored template.

Good performance of the classifier module is of high significance in the efficiency of the system. In this article, as Figure 8 shows, the output from nine classifiers has been evaluated. These classifiers include four classifiers with distance function, two radial basis function NN^[29] and probabilistic neural network^[30] classifiers, k-nearest neighbor classifier,^[31] kernel support vector machine (KSVM) classifier,^[32] and Gaussian classifier.^[33]

The efficiency of many machine learning algorithms largely depends on the metric used to measure the similarity of input patterns.^[34] Distance functions are the most common metrics used in classification. Any $D: X \times X \rightarrow (0, \infty)$ function which is satisfied by any desired value for x, y , and z such that $D(x, y) \geq 0$, $D(x, y) = 0 \leftrightarrow x = y$, $D(x, y) = D(y, x)$, and $D(x, z) \leq D(x, y) + D(y, z)$ represents a distance or metric function, while the main four distance functions for classification are as follows [Table 1].

Table 1: Distance functions

Function	Name	Expression
Dis-euc	Euclidean	$D_{\text{euc}} = \left(\sum_{i=1}^p (X_i - y_i)^2 \right)^{\frac{1}{2}}$
Dis-L1	Manhattan	$D_{L1} = \sum_{i=1}^p X_i - y_i $
Dis-Angle	Angle	$D_{\text{Ang}} = -1 * \sum_{n=1}^p \left(\frac{x_i * y_i}{\sqrt{x^2 + y^2}} \right)$
Dis-Mahal	Mahalanobis	$D_{\text{Mah}}(x) = \sqrt{(x - \mu)^T S^{-1}(x - \mu)}$

Table 2: Performance parameters

Metrics	Expression
Sensitivity	$TPR(\text{True Positive Rate}) = \frac{TP}{TP + FN} = \frac{TP}{P} = \text{Recall} = 1 - \text{FNR}$ (False Negative Rate or False Non match Rate) measures the rate of positives that are correctly identified
Specificity	$TNR(\text{True Negative Rate}) = \frac{TN}{TN + FP} = \frac{TN}{N}$ = Selectivity = 1 - FPR(False Positive Rate or False Match Rate) measures the rate of negatives that are correctly identified
PLR	$\frac{\text{Sensitivity}}{1 - \text{Specificity}} = \frac{TPR}{FPR}$ PLR, likelihood ratio positive, likelihood ratio for positive results
NLR	$\frac{1 - \text{Sensitivity}}{\text{Specificity}} = \frac{FNR}{TNR}$ NLR, likelihood ratio negative, likelihood ratio for negative results
Accuracy	$\frac{TP + TN}{TP + FN + TN + FP} = \frac{TP + TN}{P + N}$ closeness of the measurements to a specific value
Precision	$\frac{TP}{TP + FP}$ closeness of the measurements to each other

TP - True positive; FP - False positive; TN - True negative; FN - False negative; TPR - TP rate, FPR - FP rate, TNR - TN rate, FNR - FN rate, NLR: Negative likelihood ratio, PLR: Positive likelihood ratio

Table 4: Comparing results of uni-biometric and multi-instance fingerprints recognition system for 5 kernel functions with two strategies of feature fusion

Fingerprint multi-instance recognition system						
Database	Kernel function	Gaussian (%)	PolyPlus (%)	Polynomial (%)	Linear (%)	Hamming (%)
Uni-biometric Left thumbprint	Gabor Dim=73960			57%		
	Gabor + KLDA Dim-150	57	71	71	72	75
	Gabor + KPCA Dim-150	-	64	64	63	-
Uni-biometric Right thumbprint	Gabor Dim=73960			54		
	Gabor + KLDA Dim-150	54	60	60	67	69
	Gabor + KPCA Dim-150	-	60	61	67	-
Multi-instance fusion strategy	Serial Dim=147920			67		
	KLDA DM=80	71	86	86	87	87
	KPCA Dim=80	-	69	73	72	-

LDA – Linear discriminant analysis; KLDA – Kernel LDA

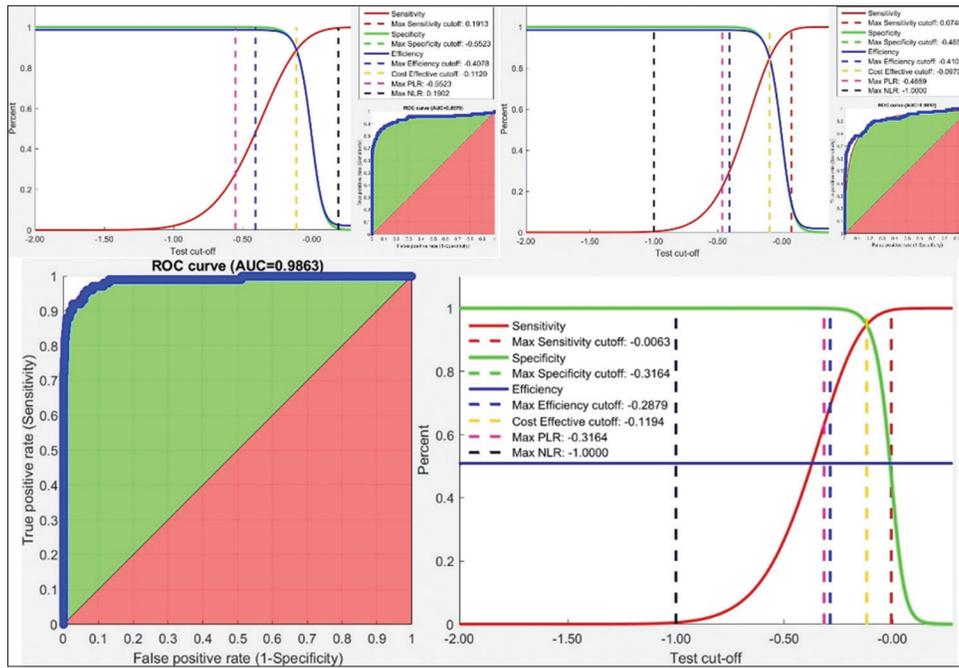


Figure 15: ROC curves of the hybrid multimodal recognition systems on Shaded face database, CASIA right and left iris databases, and Shaded fingerprint databases. ROC – Receiver operating characteristic

operations are similar to finding the weights of each individual neuron in the NN before studying the accuracy of test data classification, which would determine the efficiency of the NN. In these tests, 100 classes are envisaged for the system training and testing. For this purpose, the faces, right and left irises as well as the right and left thumbprints of 100 persons registered in the aforesaid databases were selected to extract their feature vector. Eighty percent of each person’s images (class) are utilized for training and the rest 20% for testing.

Any biometric system performance could be influenced by the size of the database and the images contained. For the proposed system, recognition accuracy, precision, receiver operating characteristic (ROC) curve, area under the ROC curve (AUC), sensitivity, recall, specificity, and efficiency are used for evaluation [Table 2] where TP = true positive,

FN = false negative, FP = false positive, and TN = true negative.

A ROC curve is developed through drawing the plot of the true-positive rate (also called as sensitivity) versus the false-positive rate (false match rate) at differing threshold settings. The false-positive rate is sometimes called as (1 – specificity). AUC denotes the probability by which the classifier determines the rank of a randomly selected positive instance above (greater than) a randomly selected negative instance (given that the “positive” rank is considered greater than “negative”). The following shows this clearly: the below curve area can be computed by (the integral boundaries are inevitably inverted because large threshold T value is lower on the X-axis):

$$AUC = \int_{x=0}^1 TPR(FPR^{-1}(x))dx \tag{7}$$

Next, the optimal performance of the introduced system is presented with performance parameters including recognition accuracy, ROC curve, AUC, sensitivity, specificity, and efficiency. The ROC curves and the verification performance are not sufficient for the validation of the multi-biometric system's overall performance. Thus, Bengio *et al.*^[38] proposed a statistical test including a half total error rate (HTER) and confidence interval (CI). Accordingly, in this study, a test of the introduced method is performed against these two parameters. Hence, the HTER can be calculated as follows:

$$HTER = \frac{FPR + FNR}{2} \quad (8)$$

To effect the computation of CI around HTER, we need to find the bound $\sigma \times z\alpha/2$. Next, σ and $z\alpha/2$ are defined as:

$$\sigma = \sqrt{\frac{FPR.TNR}{4.NI} + \frac{FNR.TPR}{4.NG}} \quad (9)$$

$$z\alpha/2 = \begin{cases} 1.645 \text{ for } 90\% \text{ CI} \\ 1.960 \text{ for } 95\% \text{ CI} \\ 2.576 \text{ for } 99\% \text{ CI} \end{cases} \quad (10)$$

where the NG and NI, respectively, stand for the total number of intra-class comparisons and the total number of inter-class comparisons.

Now, we first illustrate the results obtained from uni-biometric systems for face, iris, and fingerprint recognition separately with corresponding classifications. Furthermore, the fusion of two fingerprints as well as both right and left irises is examined in multi-instance recognition system. Finally, the results of hybrid multimodal biometric system's recognition, obtained from the features-level fusion of face, two irises, and two thumbprints, are illustrated with the same classifications.

Uni-biometric face recognition

Figure 12 illustrates the best results for face recognition by uni-biometric systems with the linear algorithms PCA, LDA, LPP, Feature Subset Selection (FSS), PDV and CCA and kernel-based non-linear algorithms kernel PCA(KPCA), KLDA, kernel Locality preserving projection (KLPP) for feature extraction on the three face databases (ORL, FERET and Shahed-University).

As expected, given internal and external variations in the FERET and Shahed University databases on the one hand and the few number of training specimens on the other, kernel-based nonlinear methods function better for feature extraction. KLDA creates a class structure to resolve partly the problems originating from the low number of samples and lack of supervision and we see better performance in the Shahed University database where the number of training specimens is limited.

Multi-instance iris recognition

To investigate the iris uni-biometric system, we consider 100 classes of the CASIA database of right and left irises and we use three images of each iris in the left iris database, two images in training and one image in testing. Moreover, in the right iris database, four iris images are used at each class, three images in training and one image in testing. The Daugman algorithm and Hough transform are utilized for iris feature extraction. A total of 9600 features are extracted for the iris, and then using the six dimensionality reduction methods of PCA, LDA, CCA, KPCA, KLDA, and KLPP, the features are down to the dimensionality of 20–150 features, whose classification results are illustrated in Figure 13.

In case the 9600 features extracted from iris are directly used for classification without any dimensionality reduction, we will obtain a maximum 93.52% recognition. Furthermore, NN classifications are virtually unusable owing to the low number of training specimens compared with the number of features. Applying nonlinear algorithms based on kernel functions with the KLDA (class structure) and the KPCA (without class structure) in the feature space would reduce dimensionality to 100 features and instead enhance recognition to 97% [Table 3].

Multi-instance fingerprint recognition

By applying eight Gabor logarithm filters to various frequencies, 73,960 features are extracted from each fingerprint, and by using kernel functions and mapping features to a higher space of kernel, nonlinear relations will be transformed into linear relations. Then, by applying LDA and PCA in the kernel Hilbert space, 73,960 fingerprint features will be reduced to 150 features which we would give to classifier as input. The results of uni-biometric system recognition for 73,960 features extracted from one fingerprint and the 150 dimensionally reduced features are shown in Table 4 after applying five kernel functions. The Hamming kernel function increases recognition to up to 75% in the KLDA class structure and to up to 69% in the KPCA nonclass structure. The fusion of features of the right and left thumbprints based on dimensionality reduction strategy would reduce dimension up to 150 features while increasing recognition to up to 87% [Figure 14].

Hybrid multimodal recognition system

Table 5 compares the results of uni-biometric systems' recognition of face, iris, and fingerprint and feature fusion in the systems of multi-instance iris and fingerprint in the kernel Hilbert space after applying five various kernel functions.

The KLDA algorithm creates a class structure through Hamming and Gaussian kernels in order to extract the best face features (93% recognition). Furthermore, this algorithm extracts the best features with poly kernel (about 95% recognition) in the iris uni-biometric system and the

Table 5: Comparing performance of uni-biometric and multi-instance systems for five kernel functions

Multi-instance recognition system	Uni-biometric face Shaded (%)		Iris multi-instance system					Thumbprint multi-instance system					
	Right CASIA (%)	Left CASIA (%)	Iris		Fusion strategy			Fingerprint		Fusion strategy			
			Right CASIA (%)	Left CASIA (%)	Serial (%)	Dimensionality reduction (%)	Right-thumb (%)	Left-thumb (%)	Serial (%)	Dimensionality reduction (%)			
Database dimensionality	100	100	100	200	200	80	100	100	200	80	100	200	80
Kernel LDA													
Gaussian	92	92.5	92.59	99.07	99.07	99.07	57	54	87	<10			
PolyPlus	71	94.44	94.44		99.07	99.07	71	60	87	87			
Polynomial	89	95.37	94.44		99.07	99.07	71	60	87	87			
Linear	89	94	94.44		100	100	72	67	87	87			
Hamming	93	94	95.37		89.81	89.81	75	69	49	49			
Kernel PCA													
Gaussian	84	64.81	63.89	100	97.22	97.22	<10	<10	62	<10			
PolyPlus	74	96.40	94.44		99.07	99.07	62	59	61	61			
Polynomial	74	96.40	94.44		50	50	62	59	61	61			
Linear	84	95.37	94.44		97.22	97.22	63	59	69	69			

LDA – Linear discriminant analysis; PCA – Principal component analysis

Table 6: Effective dimensions in the kernel Hilbert space in hybrid multimodal recognition system

Hybrid Multimodal Recognition System Fusion of Face and 2Iris and 2FP Fusion (Kernel Function)	Shaded Face Database Feature Extraction Algorithm: KLDA (function: Gaussian)					CASIA Iris Database Feature Algorithm: Daugman + KLDA (function: poly)					Shaded thumbprint Database Feature Extraction Algorithm: Gabor + KLDA (function: linear)							
	Dimensionality of Multimodal Template (Kernel Hilbert Space) (%)					Dimensionality of Multimodal Template (Kernel Hilbert Space) (%)					Dimensionality of Multimodal Template (Kernel Hilbert Space) (%)							
	1	3	5	15	35	50	80	100	150	1	3	5	15	35	50	80	100	150
Kernel LDA																		
Gaussian	<10	28	52	97	100	100	100	100	100	100	100	100	100	100	100	100	100	100
PolyPlus	<10	27	50	96	100	100	100	100	100	100	100	100	100	100	100	100	100	100
Polynomial	<10	84	99	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
Linear	<10	28	57	98	100	100	100	100	100	100	100	100	100	100	100	100	100	100
Hamming	<10	18	35	94	99	99	99	99	99	99	99	99	99	99	99	99	99	99
Kernel PCA																		
Gaussian	<10	20	57	98	100	100	100	100	100	100	100	100	100	100	100	100	100	100
PolyPlus	<10	13	33	75	77	77	77	77	77	77	77	77	77	77	77	77	77	77
Polynomial	<10	<10	<10	<10	<10	<10	<10	<10	<10	<10	<10	<10	<10	<10	<10	<10	<10	<10
Linear	<10	19	58	98	100	100	100	100	100	100	100	100	100	100	100	100	100	100

LDA – Linear discriminant analysis; PCA – Principal component analysis

Table 7: Comparing performance of nine various classifiers in hybrid multimodal recognition system

Fusion strategy		Face, Iris, and Thumbprint Hybrid Multimodal Biometric System											
Bio	Kernel function	Dim	Classification									K SVM linear function	
			Dis-Angle	Dis-L1	Dis-euc	Dis-Euk	RBFNN	PNN	KNN	Gaussian			
Kernel LDA	Face	100	93	49	93	93	93	92	93	93 ^(K-2)	93	93	
	I-Iris	100	94.44	78.70	76.85	76.85	58.33	76.85	76.85	25.93 ^(K-5)	92.59	89.82	
	L-Iris	100	91.67	12.96	10.18	10.18	<10	10.18	10.18	10.18 ^(K-2)	88.89	86.11	
	Fusion (2Iris)	80	96.30	87.96	87.96	87.96	<10	87.96	35.18 ^(K-5)	95.37	95.37		
	R-Thumb	100	72	28	72	72	72	72	72	72 ^(K-2)	72	72	
	L-Thumb	100	67	24	67	67	66	67	67	67 ^(K-3)	67	67	
	Fusion (2Thumb)	80	86	78	82	82	<10	82	82	82 ^(K-1)	87	87	
	Fusion (F _a +2I+2FP)	15	100	<10	<10	<10	<10	<10	<10	<10	92	100	
	Face	Gaussian	100	77	77	76	85	85	78	78	63 ^(K-1)	85	87
	I-Iris	PolyPlus	100	90.74	90.74	90.74	88.89	92.60	87.04	<10	88.89	91.67	
Kernel PCA	L-Iris	100	87.04	84.26	87.04	81.48	87.96	85.18	85.18	26.85 ^(K-1)	84.26	87.04	
	Fusion (2Iris)	80	95.37	94.44	95.37	93.52	95.37	94.44	94.44	57.4 ^(K-5)	22.22	86.11	
	R-Thumb	100	59	63	57	54	68	49	49	54 ^(K-1)	63	67	
	L-Thumb	100	54	59	54	47	66	40	40	48 ^(K-1)	60	62	
	Fusion (2Thumb)	100	62	69	58	61	74	54	54	44 ^(K-2)	41	70	
	Fusion (F _a +2I+2FP)	35	92	94	92	92	91	93	93	53 ^(K-1)	<10	97	
	Fusion (F _a +2I+2FP)	99	99	99	99	100	97	100	100	94 ^(K-3)	32	100	

PNN – Probabilistic neural network; KNN – k-nearest neighbors; K SVM – Kernel support vector machine; RBFNN – Radial basis function neural network; LDA – Linear discriminant analysis; PCA – Principal component analysis

beast features with linear kernel (about 70% recognition) in the fingerprint uni-biometric system. It is observed that linear functions are the best KLDA kernels for feature fusion in the iris and fingerprint multimodal systems (100% and 87%). Recognition in the KPCA nonclass structure with Gaussian and linear kernels declines 5% to 10% for face and fingerprint uni-biometric systems. However, linear function remains the best kernel for the fusion of fingerprint features.

Table 6's results show clearly the efficacy of the method proposed by this article in the face, iris, and fingerprint features' extraction and fusion in obtaining a robust and secure multimodal template. In addition to obtaining 100% recognition using the introduced method, the reduction of features to the dimensionality of 35 is highly significant. In other words, the multimodal template obtained in the proposed method by combining 147920 ($2 \times 73,960$) features pertaining to two fingerprints, 19,200 (9600×2) features pertaining to both rises, and 43,200 pixels from the face image is summarized in only 35 features. This 35 dimensionality feature vector can be a unique identifier of a person.

In Table 7, the performance of various classifiers is presented for the introduced hybrid multimodal recognition system. Taking the KLDA method and given the Poly-function, the dimensionality of only 15 features would be enough to obtain a multimodal template, so that the Dis_Angle metric classifiers and linear KSVM would bring about 100% recognition for the final decision in the hybrid multimodal biometric system. However, in the nonlinear KPCA method with Gaussian function, the length of this feature vector increases to 35 features with minor changes in recognition.

The ROC curve (AUC = 0.9988) for the proposed hybrid multi-biometric system in Figure 15 clearly illustrates the good performance of the introduced system. The feature fusion strategy in highly favorable performance of the multimodal biometric system proposed in this study is clear enough, particularly with three Dis_Angle metric classifiers, NN, and Kernel Support Vector Machine (KSVM). Even with this few number of features, there is high resolution and therefore fusion in the feature space based on the strategy of dimensionality reduction based on kernel functions is very appropriate.

Conclusion

In this article, as the feature space has richer information (higher quality and quantity) than the image and decision spaces, feature-level fusion has greater effectivity over fusion at other levels (sensor, score, and decision). Therefore, it is suggested for obtaining a robust and secure multimodal template. Out of the three proposed strategies for the fusion of feature vectors, the dimensionality reduction process with kernel methods was suggested. For the fusion of feature vectors, each feature space has to be

mapped with the appropriate kernel function based on the biometric used for that purpose. Kernel-based methods are used in transforming nonlinear problems to problems that may be resolved by a linear solution. That is why the features are mapped in the kernel Hilbert space from the original space by using an appropriate kernel function. The PCA and LDA algorithms are applied in the kernel Hilbert space for the fusion of face, iris, and fingerprint features while reducing dimensionality. In case the class structure is preserved, better results will be achieved. The proposed method is all appropriate for searching big databases (recognition uses). Therefore, it would be possible to accurately distinguish the corresponding class of a test sample in a big database of a secure multimodal template without any consistency error.

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Conflicts of interest

There are no conflicts of interest.

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