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Multimodal System by Data Fusion and Synergetic Neural Network

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Abstract

In this paper, we present the multimodal system based on the fusion of two user-friendly biometric modalities: Iris and Face. In order to reach robust identification and verification we are going to combine two different biometric features. we specifically apply 2-D discrete wavelet transform to extract the feature sets of low dimensionality from iris and face. And then to obtain Reduced Joint Feature Vector(RJFV) from these feature sets, Direct Linear Discriminant Analysis (DLDA) is used in our multimodal system. In addition, the Synergetic Neural Network(SNN) is used to obtain matching score of the preprocessed data. This system can operate in two modes: to identify a particular person or to verify a person's claimed identity. Our results for both cases show that the proposed method leads to a reliable person authentication system.

Key words : multimodal system, feature fusion, RJFV, DLDA, synergetic classifier

1. Introduction

Biometric authentication, which identifies an individual person using physiological and/or behavioral characteristics, such as iris, face, fingerprints, hand geometry, handwriting, retinal, vein, and speech, is one of the most reliable and capable than knowledge-based(e.g., password) or token-based (e.g., a key) techniques, since biometric features are hardly stolen or forgotten. However, recognition based on any one of these modalities may not be sufficiently robust or else may not be acceptable to a particular user group or in a particular situation or instance.

Current approaches to the use of single biometrics in personal identity authentication are therefore limited, principally because no single biometric is generally considered both sufficiently accurate and user-acceptable for universal application. Multimodal biometrics can provide a more balanced solution to the security and convenience requirements of many applications[1], [2], [3]. However, such an approach can also lead to additional complexity in the design and the management of authentication systems. Additionally, complex hierarchies of security levels and interacting user/provider requirements demand that a system is adaptive and flexible in configuration.

There are three main strategies to build multimodal biometric systems. The first method is to apply decision fusion which means combining accept or reject decisions of unimodal systems[4]. The other method to construct a multimodal system is to use the feature fusion. This means that features extracted by multiple sensors are concatenated. As the features extracted from one biometric trait are independent of those extracted from the other, it is reasonable to concatenate the two vectors into a single new vector. The new feature vector now has a higher dimensionality and represents a person's identity in a different hyperspace. Feature reduction techniques may be employed to extract useful features from the larger set of features. Finally there is the matching score level fusion which means combining matching scores reported by multiple matchers. These techniques attempt to minimize the False Rejection Rate(FRR) for a given False Acceptance Rate(FAR)[5].

Our methodology to build multimodal biometric system focuses on the Feature level fusion using face information in combination with iris. Iris and face can be used efficiently in multimodal system because face recognition is friendly and non-invasive whereas iris recognition is one of the most accurate biometrics[1]. When we construct the multimodal system using the feature fusion, one of the most important things we have to consider a dimensionality of the biometric feature set. It has a disadvantage that the size of the combined feature set is normally large. In recognition systems using the biometric features, one may try to use a large feature set to enhance the recognition performance. However, the increase in the number of the biometric features has caused other problems. For example, the recognizer using higher dimension feature set requires more parameters to characterize the classifier and requires more storage. Thus, it will increase the complexity of computation and make its real-time implementation more difficult and costly. Furthermore, a larger amount of data is needed for training. The system we propose is given in Fig.1 and the dimensionality of the biometric feature set is reduced efficiently in each step.

This paper is organized as follows. In section 2, we overview a multilevel two-dimensional Discrete Wavelet Transform (DWT) to extract feature vectors from the iris and face images. From the two biometric feature vectors, we will form a Joint Feature Vector(JFV). we also describe the Direct Linear Discriminant Analysis(DLDA) scheme[6] to linearly

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transform the joint feature vector to new feature space with higher separability and lower dimensionality. The same operations of DWT and DLDA are performed in training as well as testing phases. Section 3 describes feature matching approach based on Synergetic Neural Network(SNN). Experimental results and analysis will be stated in section 4, and finally the conclusions are given in section 5.

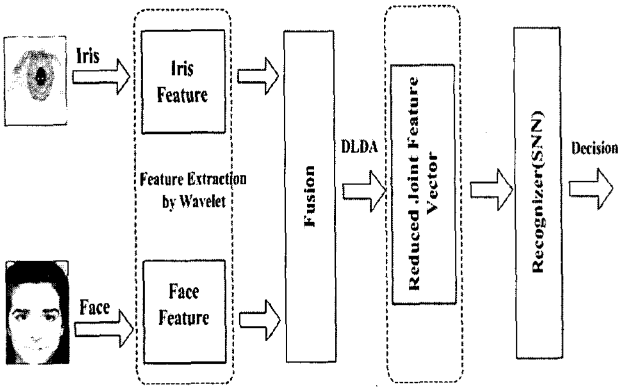


Fig. 1. Bimodal biometric system using Iris and Face.

2. Feature Extraction

Most applications emphasize finding a feature set that produces efficient and implementable results. If the dimension of features defining a problem is too high, we must select a robust set of features from an initial set to provide appropriate representation. We have chosen the DWT and DLDA approach to obtain a robust and lower dimensional set of features with high discriminating power. Our previous work has already shown that the DWT+DLDA approach can be successfully used on unimodal biometric data[8].

2.1 Wavelet Transform

The hierarchical wavelet functions and its associated scaling functions are to decompose the original signal or the image into different subbands. The decomposition process is recursively applied to the subbands to generate the next level of the hierarchy. The traditional pyramid-structured wavelet transform decomposes a signal into a set of frequency channels that have narrower bandwidths in the lower frequency region[9]. The DWT was applied for texture classification and image compression because of its powerful capability for multiresolution decomposition analysis. The wavelet decomposition technique can be used to extract the intrinsic features for the recognition of persons by their biometric data. We employ the multilevel 2D Daubechies wavelet transform to extract the iris and face features. Using the wavelet transform, we decompose the image data into four subimages via the high-pass and low-pass filtering with respect to the column vectors and the row vectors of array pixels. Fig.2 shows the process of pyramid-structured wavelet decomposition.

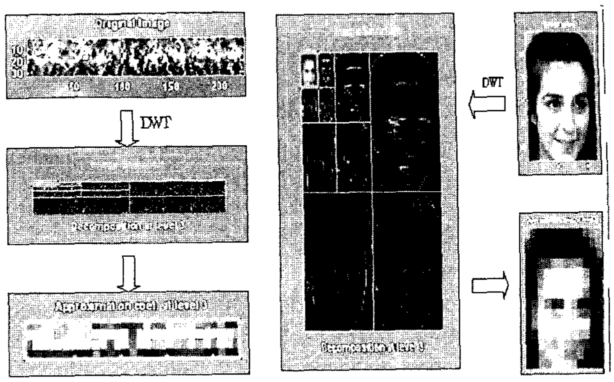


Fig. 2. Example of a three-level wavelet transform of the iris and face images.

In this paper, we use the statistical features and the two or three-level lowest frequency subimage to represent unimodal biometric feature vectors, thus statistical features were computed from each subband image. First, we divide the subimages into local windows in order to get robust feature sets against shift and noisy environment. Next, we extract first-order statistics features, that is, mean and standard deviation from local windows on the corresponding subimages to represent feature vectors. Generally, the mean extracts low spatial-frequency features and the standard deviation can be used to measure local activity in the amplitudes from the local windows[10]. Also, low frequency components represent the basic figure of an image, which is less sensitive to varying images. The feature vectors composed of these features include both local and global information . The level of low frequency subimage chosen to extract the feature vector depends on size of the image. If the size is smaller than our localized iris image and ORL face, the one or two-level lowest frequency subimage might have higher discriminating power. That is the reason why we choose three-level decomposition on the iris image and ORL face and two-level on the IIS face.

After extraction of the iris and face feature vector x by wavelet transform, each biometric image vector of high dimension is transformed to the low dimensional feature vector. For fusion we use concatenation between the iris and face feature vectors. So we can form a Joint Feature Vector(JFV) y and construct biomodal model using JFV. However, the dimensionality of JFV is too high to reduce the recognition time and save memory.

2.2 Direct Linear Discriminant Analysis

To reduce the feature dimensionality further and to enhance the class discrimination, we apply the Direct Linear Discriminant Analysis(DLDA). By using DLDA, we can extract a Reduced Joint Feature Vector(RJFV) z with higher discriminating power and lower dimensionality then the Joint Feature Vector(JFV) y.

Existing LDA methods first use PCA to project the data into lower dimensions, and then use LDA to project the data into an even lower dimension[11]. The PCA step, however, can remove those components that are useful for discrimination. The key idea of DLDA method is to discard the null space of between-class scatter S_b - which contains no useful information - rather than discarding the null space of S_w, which contains the most discriminative information[6]. Each scatter is given as follows:

$$S_b = \sum_{i=1}^{J} n_i(\mu_i - \mu)(\mu_i - \mu)^T$$
$$S_w = \sum_{i=1}^{J} \sum_{x \in C_i} (x - \mu_i)(x - \mu_i)^T$$

where n_i is the number of JFVs in class i, μ_i is the mean of class i, μ is the global mean, and J is the number of classes.

The DLDA method is outlined below. We do not need to worry about the computational difficulty when both scatter matrices are too big to be held in memory because the dimensionality of input data is properly reduced by wavelet transform.

First, we diagonalize the S_b matrix by finding a matrix V such that

$$V^T S_b V = D$$

where the columns of V are the eigenvectors of S_b and D is a diagonal matrix that contains the eigenvalues of S_b in decreasing order. It is necessary to discard eigenvalues with 0 value and their eigenvectors, as projection directions with a total scatter of 0 do not carry any discriminative power at all [6].

Let Y be the first m columns of V (an $n \times m$ matrix, n being the feature space dimensionality),

$$Y^T S_b Y = D_b \qquad (\, m \times m \text{ matrix})$$

where D_b contains the m non-zero eigenvalues of S_b in decreasing order and the columns of Y contain the corresponding eigenvectors.

The next step is to let $Z = YD^{1/2}$ such that $Z^T S_b Z = I$. Then we diagonalize the matrix $Z^T S_w Z$ such that

$$U^T (Z^T S_w Z) U = D_w \tag{1}$$

where $U^T U = I$. D_w may contain zeros in its diagonal. We can sort the diagonal elements of D_w and discard some eigenvalues in the high end, together with the corresponding eigenvectors.

We compute the LDA matrix as $A = U^T Z^T$. Note that A diagonalizes the numerator and denominator in Fisher's criterion.

Finally, we compute the transformation matrix(2) that takes an $n \times 1$ feature vector and transforms it to an $M \times 1$ feature vector.

$$Z_{reduced} = D_b^{-1/2} A y \tag{2}$$

where z is a Reduced Joint Feature Vector and y is a Joint Feature Vector.

3. Synergetic Learning Algorithm

In the late 1960s, Haken, an outstanding German scientist, introduced the basic concept of synergetics : an interdisciplinary field of research that is concerned with the spontaneous formation of macroscopic spatial, temporal, or functional structures of system via self-organization[12],[13]. There are large classes of system in wich self-organization obeys the same basic principles. When a system undergoes qualitative macroscopic changes, synergetics is applied as mathematic means to describe this process. In the 1990s, Haken presented a new concept which applies synergetics to pattern recognition. Considering the similarity between pattern recognition and pattern formation, he presented an important viewpoint:the process of pattern recognition is actually the process of pattern formation. Synergetics offers a new and different approach to the construction of highly parallel scheme for pattern recognition and decision making, so in contrast to neural networks in which construction is done - from bottom to up - synergetic pattern recognition(SPR) allows the algorithm scheme from top to bottom[14],[15].

The Synergetic classifier relies on an orthonormal basis of m-dimensional adjoint vectors $\mathbf{c}_{k^+}$ for the prototype features $\mathbf{c}_k$. As the prototype feature vectors, we use the mean vectors of RJFVs in each class. All vectors $\mathbf{c}_k$ are normalized and centered, so that they satisfy the following two condition:

$$\sum_{j=1}^{M} \mathbf{c}_{kj} = 0, \quad \sum_{j=1}^{M} \mathbf{c}_{kj^2} = 1, \qquad k = 1, 2, \cdots, J \tag{3}$$

where J is the number of classes.

Adjoint prototypes $\mathbf{c}_k^+$ must obey the condition: $\mathbf{c}_k^+ \cdot \mathbf{c}_{k'} = \delta_{kk'}$ where δ denotes the Kronecker delta symbol with $\delta_{kk'} = 1$ if $k = k'$, 0 else. To achieve this, each adjoint prototype vector can be written as:

$$\mathbf{c}_k^+ = \sum_{k'=1}^{J} a_{kk'} \mathbf{c}_{k'}, \qquad k = 1, 2, \cdots, J \tag{4}$$

where J is the number of classes. Define the matrices A, C and C^+ as

$$A := (a_{kk'}) \qquad (\, J \times J \text{ matrix})$$
$$C := (\mathbf{c}_1 \ \ \mathbf{c}_2 \ \cdots \ \ \mathbf{c}_J) \qquad (\, M \times J \text{ matrix})$$
$$C^+ := (\mathbf{c}_1^+ \ \ \mathbf{c}_2^+ \ \cdots \ \ \mathbf{c}_J^+) \qquad (\, M \times J \text{ matrix})$$

By (4), we can write

$$C^+ = CA^T \tag{5}$$

where C^+ is a matrix with the adjoint prototype vectors as its columns.

To compute the adjoint prototypes $\mathbf{c}_k^+$, we should know he values of parameters $a_{kk'}$.

Let us multiply (5) by C^T. Then

$$C^T C^+ = C^T C A^T = I, \tag{6}$$

by the condition: $\mathbf{c}_k^+ \cdot \mathbf{c}_{k'} = \delta_{kk'}$ where δ denotes the Kronecker delta symbol. Therefore parameters $a_{kk'}$ are obtained by solving $A=(P^{-1})^T$ where $P=C^TC$.

If V is not invertible matrix, we can't have the values of parameters $a_{kk'}$. In this case, we will use $\mathcal{P}^{-1}$ obtained by following Lemma 1 instead of P^{-1}.

Lemma 1. *Let P be an $m\times n$ matrix with rank r. Then there exists an $m\times n$ diagonal matrix Σ of the form*

$$\Sigma = \begin{bmatrix} D & 0 \\ 0 & 0 \end{bmatrix} \tag{7}$$

where the diagonal entries in D are the first r singular values of P, $\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_r > 0$, and there exist an $m\times r$ matrix U_r and an $n\times r$ matrix V_r such that

$$\mathcal{P}^{-1} = V_r D^{-1} U_r^T$$

Proof) Let λ_i and v_i be eigenvalues, where $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n$, and eigenvectors of P^TP, respectively. $\{A\,\mathbf{v}_1, \cdots, \mathrm{A}\,\mathbf{v}_r\}$ is an orthogonal basis for Col A. Normalize each $A\,\mathbf{v}_i$ to obtain an orthonormal basis $\{\mathbf{u}, \cdots, \mathbf{u}_r\}$, where

$$\mathbf{u}_i = \frac{1}{\|P\,\mathbf{v}_i\|} P\,\mathbf{v}_i = \frac{1}{\sigma_i} P\,\mathbf{v}_i$$

and

$$P\,\mathbf{v}_i = \sigma_i \mathbf{u}_i \qquad (1 \leq i \leq r) \tag{8}$$

Now extend $\{\mathbf{u}_1, \cdots, \mathbf{u}_r\}$ to an orthonormal basis $\{\mathbf{u}, \cdots, \mathbf{u}_m\}$ of R^m, and let

$$U = [\,\mathbf{u}_1 \;\; \mathbf{u}_2 \cdots \;\; \mathbf{u}_m] \text{ and } V = [\,\mathbf{v}_1 + \mathbf{v}_2 \cdots \;\; \mathbf{v}_m]$$

By construction, U and V are orthogonal matrices. Also, from (8), $PV = [P\,\mathbf{v}_1 \cdots P\,\mathbf{v}_r\, 0 \cdots 0] = [\sigma_1 \mathbf{u}_1 \cdots \sigma_r \mathbf{u}_r\, 0 \cdots 0]$.

Let D be the diagonal matrix with diagonal entries $\sigma_1, \cdots, \sigma_r$, and let Σ be as in (7) above. Then

$$U\Sigma = [\mathrm{u}_1 \;\; \mathrm{u}_2 \;\; \mathrm{L} \;\; \mathrm{u}_m] \left[\begin{array}{ccc|c} \sigma_1 & & 0 & \\ & \sigma_2 & & 0 \\ & \mathrm{O} & & \\ 0 & & \sigma^r & \\ \hline & 0 & & 0 \end{array}\right]$$

$$= [\sigma_1 \mathbf{u}_1 \cdots \sigma_r \mathbf{u}_r\, 0 \cdots 0]$$
$$= PV$$

Since V is an orthogonal matrix, $U\Sigma V^T = PVP^T = P$. When Σ contains row or columns of zeros, a more compact decomposition of P is possible. Let us partition U and V into submatrices whos first blocks contain r columns:

$$U = [\,U_r \;\; U_{m-r}], \qquad \textit{where } U_r = [\,\mathbf{u}_1 \cdots \;\; \mathbf{u}_r]$$
$$V = [\,V_r \;\; V_{n-r}], \qquad \textit{where } V_r = [\,\mathbf{v}_1 \cdots \;\; \mathbf{v}_r].$$

Then U_r is $m\times r$ matrix and V_r is $n\times r$ matrix. The partitioned matrix multiplication shows that

$$P = [\,U_r \;\; U_{m-r}] \begin{bmatrix} D & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} V_r^T \\ V_{n-r}^T \end{bmatrix} = U_r D V_r^T.$$

Since the diagonal entries in D are nonzero, we can form the following matrix:

$$\mathcal{P}^{-1} = V_r D^{-1} U_r^T \qquad ■$$

After having computed the adjoint prototypes $\mathbf{c}_k^T$ by (5), classification of a test pattern t having the same dimension with $\mathbf{c}_k^+$ isdone by building order parameters O_k as follows:

$$O_k = \mathbf{c}_k^+ \cdot t.$$

The maximum value of order parameter O_k classifies test pattern t into class k.

4. Experinental Results

4.1 Biometric Database

▶Face Database

• **ORLFace** We used face images from Olivetti-Oracle Research Lab(ORL)[16]. The ORL data set consists of 400 frontal faces: 10 tightly cropped images of 40 subjects with variations in poses, illuminations, facial expressions and accessories. The size of each image is 92×112 pixels, with 256 grey levels per pixel.

• **IISFace** The IIS face database is accessible at http://smart.iis.sinica.edu.tw/index.html [17]. We sampled frontal face images of 100 subjects from the IIS face database, each subject having 10 images with various expressions. The size of each image is 60×60 pixels, with 256 grey levels per pixel.

▶Iris Database

Eye images were acquired through CCD camera with LED (Light-Emitting Diode) lamp around lens under indoor light. The size of eye images is 320×240 pixels with 256 grey intensity values, and the size of normalized iris images is 225×32 pixels.

• **Iris1** This data set consists of 1000 iris images acquired from 100 individuals. They are iris images which pass Image Quality Checking Step(IQCS).

• **Iris2** Iris2 is composed of 400 iris images sampled from Iris1 to combine with ORLFace.

4.1 Identification and Verification Results on Each Database

In this work, we randomly chose five images per person for training from face and iris, the other five for testing. To reduce variation, each experiment was repeated 20 times.

Table1. shows the identification rates of unimidal and multimodal systems vs. dimension of biometric feature for IISFace and Iris data. Table2. shows the results for ORLFace and Iris data.

As can be seen from Table1. and 2., the multimodal systems using RJFVs of face and iris outperform the unimodal systems. The identification rates for IIS+Iris1 is 99.09% over 35 feature dimension. For ORL+Iris2 , it is 99.85% over 25 and feature dimension. It shows that the multimodal system using RJFVs can achieve much better identification rate over much lower feature dimension than unimodal system. In addition, the best Identification rates of the IIS+Iris1 and ORL+Iris2 are 99.57% and 100% with 70 and 35 features, respectively.

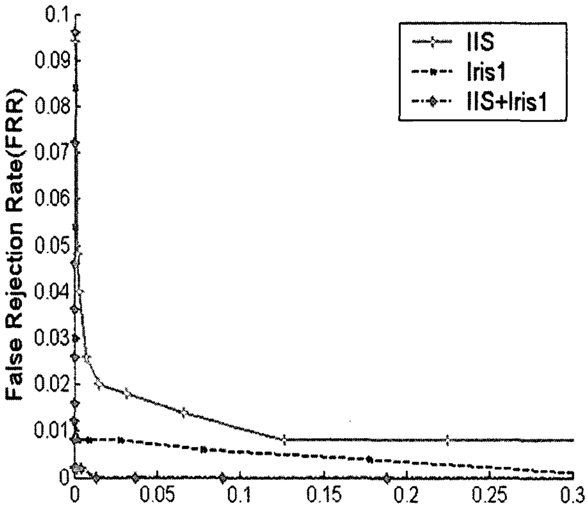
Table 1. Person identification rate for IISFace and Iris data(%).

Feature Dimension	IIS	Iris1	IIS+Iris1
30	91.92	97.83	98.64
35	93.13	98.33	99.09
40	94.54	98.47	99.32
45	94.83	98.38	99.41
50	94.83	98.78	99.49
55	94.89	98.41	99.51
60	94.77	98.52	99.48
65	94.7	98.31	99.44
70	94.77	97.93	99.57
75	93.83	97.81	99.46
80	93.17	97.57	99.25
85	91.83	97.21	99.16
90	90.68	96.72	98.96

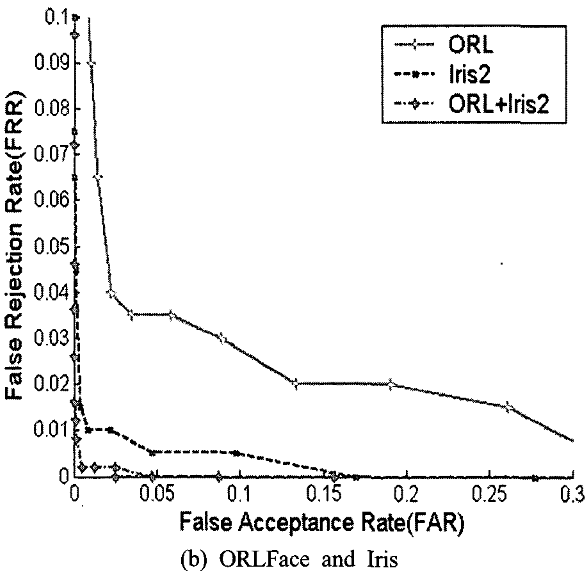
Table 2. Person identification rate for ORLFace and Iris data(%).

Feature Dimension	ORL	Iris2	ORL+Iris2
5	23.6	24	26.23
10	63.6	73.3	73.95
15	81.6	92.4	94.08
20	88.25	96.5	98.65
25	93.5	99.2	99.85
30	91.6	98.7	99.98
35	89.72	98.3	100
39	89.79	97.9	100

Two commonly used error measures for a verification system are False Acceptance Rate(FAR) - an imposter is accepted - and False Rejection Rate(FRR) - a client is rejected. If one wants to compare different biometric systems, it is problematic since value "similarities" or, inversely, "distances" are defined very differently, and therefore threshold values often have incomparable meanings. This difficulty is avoided by Receiver Operating Characteristic(ROC) Curve, in which the similarity threshold parameter is eliminated and FRR is seen as a function of FAR.

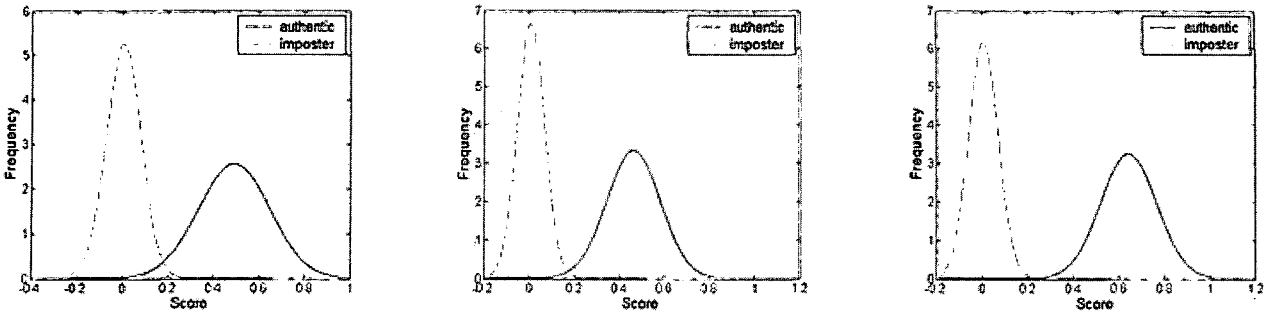


(a) IISFace and Iris

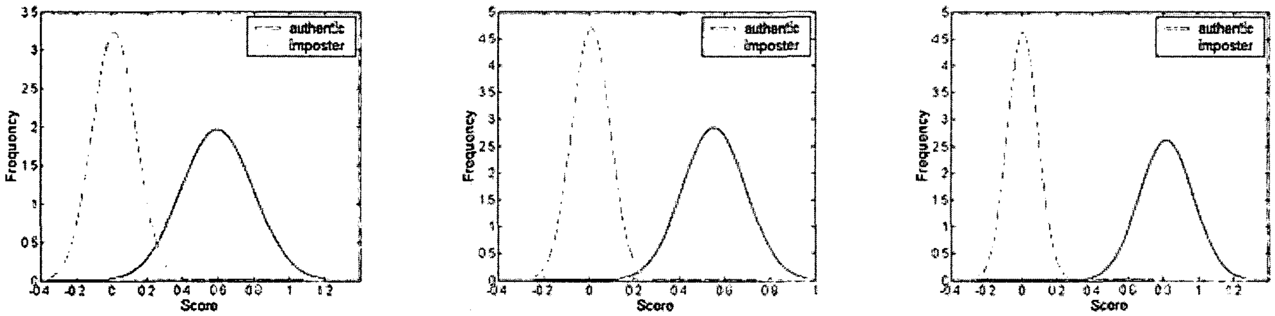


(b) ORLFace and Iris

Fig. 3. Receiver Operating Characteristic(ROC) Curves.



(a) (b) (c)
Fig. 4. Distribution of matching score of (a) IISFace, (b) Iris1, (c) IISFace+Iris1.



(a) (b) (c)
Fig. 5. Distribution of matching score of (a) ORLFace, (b) Iris2, (c) ORLFace+Iris2.

The results of the person verification experiments are shown in Fig.3. We can also see the multimodal systems by data fusion outperform the unimodal systems in verification mode. The range of threshold values that can be selected for high verification rates is larger for the bimodality compared to the single modalities. This result can also be found from the distribution of matching scores in Fig.4 and Fig.5 Our proposed system can provide users with strong authentication and enhanced convenience for security and reduce verification time.

5. Conclusion

In this paper, we have shown that the use of data fusion allows to improve significantly the performance of multimodal identification systems. We have also shown that Iris and face can be used efficiently in multimodal system. The grey-level images of iris and face can be simultaneously acquired and used to achieve the performance that may not be possible by single biometric alone. In addition, the DWT+DLDA method has been used to obtain the Reduced Joint Feature Vectors(RJFV) with higher discriminating power and lower dimensionality. These methods of feature extraction well suit with multimodal system as well as unimodal system while allowing the algorithm to be translation and rotation invariant.For future works, it is necessary to conduct experiments on a large number of data so as to verify the efficiency and robustness of our approach.

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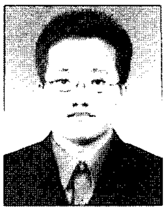

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