Represent and fuse bimodal biometric images at the feature level: complex-matrix-based fusion scheme

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Abstract. Multibiometrics can obtain a higher accuracy than the single biometrics by simultaneously using multiple biometric traits of the subject. We note that biometric traits are usually in the form of images. Thus, how to properly fuse the information of multiple biometric images of the subject for authentication is crucial for multibiometrics. We propose a novel image-based linear discriminant analysis (IBLDA) approach to fuse two biometric traits (i.e., bimodal biometric images) of the same subject in the form of matrix at the feature level. IBLDA first integrates two biometric traits of one subject into a complex matrix and then directly extracts low-dimensional features for the integrated biometric traits. IBLDA also enables more information to be exploited than the matching score level fusion and the decision level fusion. Compared to linear discriminant analysis (LDA), IBLDA has the following advantages: First, it can overcome the small sample size problem that conventional LDA usually suffers from. Second, IBLDA solves the eigenequation at a low computational cost. Third, when storing the scatter matrices IBLDA will not bring as heavy a memory burden as conventional LDA. We also clearly show the theoretical foundation of the proposed method. The experiment result shows that the proposed method can obtain a high classification accuracy.
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Subject terms: biometric images; feature extraction; feature level fusion; multibiometrics.

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1 Introduction

Biometrics, which focuses on identifying personal identities using static characters, such as the face, palmprint, fingerprint, or dynamic traits (such as voice or signature) of the individuals, is attracting increasing attention of the researchers in the area of computer science.[1,2] It has been proved that the use of multimodal biometric traits of individuals can achieve a higher accuracy than the use of single biometric.[1,3–7] Because biometric traits are usually in the form of images, hereafter we refer to biometric traits as biometric images. The system, which uses two biometric images to perform identity authentication, is a special form of the multimodal biometric system. Hereafter, this kind of systems is referred to as a two-biometric-image system (TBIS). TBIS uses the fewest biometric images yet possesses the basic characteristics of a multimodal biometric system. Available research works on this kind of system include biometrics using face and fingerprint,[8,9] iris and face,[10] ear and face,[11] palmprint and hand geometry,[12] face and speech data,[13] etc. We note that the two biometric images that can be integrated for identity authentication also include two biometric images from the same body surface organ, such as the left and right palmprint images, the visible-light and the infrared images of the face, the images of the left and right ears, etc. This paper is confined to feature extraction of the TBIS. As we know, how to properly fuse the available biometric images is one important aspect of TBIS and multibiometrics. Widely used fusion approaches to biometric images include feature level fusion, matching score level fusion and fusion at the decision level fusion.[14–18] Advantages and characteristics of fusion at different levels can be briefly presented as follows:[19] the main advantage of decision level fusion is easy implementation. However, unlike feature level and matching score level fusion, decision level fusion does not enable information of multiple biometric traits to be fully exploited. Indeed, decision fusion for verification can fuse only the "accept" or "reject" decisions associated with different biometric traits and decision fusion for identification fuses only the class label decisions corresponding to different biometric traits. It is commonly considered that fusion at the decision level does not have the same potential to improve the overall system performance as fusion at the matching score level or at the feature level. Fusion at the matching score level fuses multiple biometric traits at an earlier stage than fusion at the decision level and can exploit more information generated from the multiple biometric traits. Because fusion at the feature level fuses multiple biometric traits at the most early stage, it allows these traits to be fully exploited for personal authentication. Actually, fusion at the feature level can convey the richest biometric

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information.[18] However, it seems that researchers pay more attention to the matching score level fusion than to the feature level fusion and much literature of matching score level fusion are available.[19–22]

Feature extraction is an important aspect of a recognition system. Linear discriminant analysis (LDA) has been widely used in feature extraction of biometrics and other classification problems.[23–27] Feature extraction is also a necessary component of TBIS. LDA aims to transform original patterns into a lower dimensional space with the maximum between-class separability. However, as we know, LDA was originally developed for only a one-dimensional signal. When LDA is applied for feature extraction of image data, it should convert the image matrix into a one-dimensional vector in advance. Consequently, the between-class scatter matrix and the within-class scatter matrix are usually so high dimensional that the computational cost of solving the transforming axes is quite high. For example, if the image is a 200 by 100 matrix, then LDA has the 20,000 by 20,000 between-class and within-class scatter matrix. Moreover, because in the applications on image recognition the number of training patterns is usually smaller than the dimensionality of the scatter matrix, it is not easy to accurately evaluate the scatter matrix.[27] Additionally, LDA may also encounter the small sample-size problem. In other words, because the number of the training pattern is smaller than the dimension of the scatter matrix, the within-class scatter matrix is usually singular and the corresponding eigenequation cannot be directly solved.

One noticeable extension of the LDA technique is the complex LDA method.[26] Complex LDA can extract features from complex vectors, whereas the original LDA can perform feature extraction for only real vectors. However, for image-based application, the complex LDA method also usually suffers from the SSS problem, in which the eigenequation cannot be directly solved due to its non-invertible high-dimensional within-class scatter matrix. In order to overcome the shortcoming of LDA, the two-dimensional discriminant transform[27] (TDDT) has been developed. This technique is also based on the LDA methodology and can efficiently and directly extract features from image matrices. On the other hand, it seems that a simple implementation scheme of TDDT is not able to fully exploit the discriminant information of matrix data.[28]

In this paper, we develop a novel feature extraction method [i.e., image-based LDA (IBLDA)]. This method combines the two biometric images of the same subject at the feature extraction level and can directly extract features from the two biometric images in the form of a matrix. Additionally, IBLDA provides a novel and simple feature extraction and feature fusion method for two biometric images; it also has a solid theoretical foundation. Moreover, IBLDA has the following advantages: First, it directly exploits the biometric image data to perform feature extraction, whereas LDA should convert the matrix data into a high-dimensional one-dimensional vector in advance. Second, when solving the eigenequation, IBLDA needs a low computational cost. Third, because IBLDA has lower-dimensional scatter matrices, it does not bring as heavy a memory burden as conventional LDA. Moreover, it is also remarkable that IBLDA integrates two biometric images in a very simple and intuitive way. Indeed, while IBLDA fuses two biometric images at the feature level, it also serves as the feature extraction procedure of TBIS. As presented earlier, fusion at the feature level can enable the two biometric images to be fully exploited for identity authentication. Experiments show that our method is mathematically tractable and computationally efficient while achieving a high classification accuracy.

The remainder of this paper is organized as follows: In Section 2, we present the idea of IBLDA. In Section 3, we formally describe IBLDA in detail. In Section 4, we present the experiments on one face data set, including visible-light and near-infrared images, and one ear data set, including the left and right ear images. Finally, we offer the conclusion and discussion in Section 5.

2 Idea of IBLDA

As we know, in a biometric system the biometric image is usually represented by images, as does each of the biometric images of TBIS. For example, there are face images, palmprint images, fingerprint images, retinal images, and so on. If we can directly and simultaneously perform feature extraction for the two biometric images of a subject, then the feature extraction process will be convenient and efficient. In this paper, we first use complex matrices to denote the subjects in the TBIS. For instance, we can combine the two images denoting the left ear image and the right ear image of one individual to form a complex matrix. We then develop a novel method to directly extract features from the complex matrix. We refer to the method as IBLDA because this method employs a methodology analogous to LDA and is directly applicable to the two biometric images in the form of image data.

The difference between the LDA technique and IBLDA is as follows: Before LDA is applied to image matrices, images should be transformed into one-dimensional data. Consequently, the obtained covariance matrix is very high dimensional, which means that a large size of memory is required to store it. Moreover, it is difficult to accurately evaluate this high-dimensional matrix using a small number of training patterns.[29] On the contrary, IBLDA has much lower dimensional scatter matrices than LDA. As a result, the transforming axes of IBLDA can be worked out more computationally efficiently than those of naive LDA. Another advantage of IBLDA is that it can simultaneously extract features from the two biometric images of TBIS. Section 3 will present IBLDA in detail.

3 Description of IBLDA

3.1 *Formal Presentation of IBLDA*

Let A and B denote the two matrices representing the two biometric images of one subject. Suppose that A and B have the same dimension, then we can define a complex matrix $C=A+iB$ to represent this subject. C is also referred to as a pattern that consists of two biometric images. In this way, a complex matrix can formally simply represent two biometric images of one subject without information loss.

We define the between-class scatter matrix G_{b} and the within-class scatter matrix G_{w} of IBLDA as follows:

$$G_{\mathrm{b}} = \frac{1}{L}\sum_{p=1}^{L} (\bar{C}_p - \bar{C})^H(\bar{C}_p - \bar{C}), \tag{1}$$

$$G_{\mathrm{w}} = \frac{1}{rL}\sum_{p=1}^{L}\sum_{j=1}^{r} (C_p^j - \bar{C}_p)^H(C_p^j - \bar{C}_p), \tag{2}$$

where $\bar{C}$ is the mean of all training patterns, $\bar{C}_p$ denotes the mean of all the training patterns of the p'th category, and L is the number of categories. Both G_{b} and G_{w} are complex matrices. The superscript H denotes the conjugate transpose of the complex matrix. C_p^j represents the j'th training pattern of the p'th class.

We explain the IBLDA-based feature extraction procedure as follows. If X is a transforming axis, in the form of complex vector, that is generated from IBLDA, then the complex matrix C can be transformed into a complex vector $\mathbf{Z}$ by $\mathbf{Z}=CX$. $\mathbf{Z}$ is referred to as a feature of C. $\mathbf{Z}$ is also a complex vector. It should be pointed out that one transforming axis can produce only one feature. If the feature-extraction procedure requires only one feature (i.e., the complex matrix representing the subject needs to be transformed into only a complex vector), then we take as X the eigenvector corresponding to the largest eigenvalue of the following eigenequation:

$$G_{\mathrm{b}}X = \lambda G_{\mathrm{w}}X. \tag{3}$$

On the other hand, if the feature-extraction procedure needs t transforming axes to transform the complex matrix into a new complex matrix consisting of t complex vectors, we take the t eigenvectors corresponding to the first t largest eigenvalues of (3) as the needed t transforming axes. Suppose that the needed t transforming axes are $X_1, X_2, \ldots, X_t$, respectively. Let $Y=[X_1X_1\ldots,X_t]$, then we can extract features from pattern C using $A=CY$. If C is an m by n complex matrix, then the feature extraction result A is an m by t complex matrix. Because $t \leqslant n$, we can say that IBLDA uses the linear transform to convert C into lower dimensional features.

The underlying rationale of IBLDA can be shown as follows. According to the definitions of G_{b} and G_{w}, we can prove that in the new space obtained using the transforming axis X, the within-class variance of the patterns is $\mathbf{Z}^H G_{\mathrm{w}}\mathbf{Z}$, while the variance of the means of different classes can be expressed as $\mathbf{Z}^H G_{\mathrm{b}}\mathbf{Z}$. We can demonstrate this concisely as follows: As shown above, $\mathbf{Z}$ denotes the feature of a pattern with respect to the transforming axis X. Let $\bar{Z}$ denote the mean of the features of the total training patterns. Let $\bar{Z}_1, \bar{Z}_2, \ldots, \bar{Z}_L$ stand for the means of the features of all the categories, respectively. We can define the mean v_{w} of the within-class variance (i.e., the variance of the features of patterns from the same category) as

$$v_{\mathrm{w}} = \frac{1}{rL}\sum_{p=1}^{L}\sum_{j=1}^{r} (Z_p^j - \bar{Z}_p)^H(Z_p^j - \bar{Z}_p), \tag{4}$$

where $\bar{Z}_p$ and Z_p^j denote the mean of the pattern features of the p'th category and the j'th pattern feature of the p'th category, respectively.

Lemma 1. v_{w} is identical to $X^H G_{\mathrm{w}} X$.

Proof. Because $\bar{Z}_p=\bar{C}_pX$, $Z_p^j=C_p^jX$, we have $v_{\mathrm{w}} =(1/rL)\Sigma_{p=1}^{L}\Sigma_{j=1}^{r}(C_p^jX-\bar{C}_pX)^H(C_p^jX-\bar{C}_pX)$. Furthermore, we can transform v_{w} into $v_{\mathrm{w}}=(1/rL)\Sigma_{P=1}^{L}\Sigma_{j=1}^{r}X^H(C_p^j -\bar{C}_p)^H(C_p^j-\bar{C}_p)X=X^H G_{\mathrm{w}}X$. Thus, the proof is complete.

In the new space, the variance of the means of different classes, which is referred to as the between-class variance, can be defined as

$$v_{\mathrm{b}} = \frac{1}{L}\sum_{p=1}^{L} (\bar{Z}_p - \bar{Z})^H(\bar{Z}_p - \bar{Z}). \tag{5}$$

Lemma 2. v_{b} is identical to $X^H G_{\mathrm{b}} X$.

The proof of this lemma is similar to that of Lemma 1.

According to the nature of the LDA methodology, the optimal transforming axis should make patterns from different classes in the new space have the best linear separation and make the patterns from the same class have the minimum difference. In other words, if X is the optimal transforming axis, the ratio of the between-class variance to the within-class variance (i.e., $X^H G_{\mathrm{b}}X / X^H G_{\mathrm{w}}X$) should reach its maximum value. We also say that, when solving the optimal transforming axis for IBLDA, we have the objective function $\arg\max_X X^H G_{\mathrm{b}}X / X^H G_{\mathrm{w}}X$.

Theorem 1. The X that maximizes the objective function $\arg\max_X X^H G_{\mathrm{b}}X / X^H G_{\mathrm{w}}X$ should be the eigenvector corresponding to the largest eigenvalue of Eq. (3).

Proof. It is clear that $X^H G_{\mathrm{b}}X / X^H G_{\mathrm{w}}X$ and the Lagrangian function $L(X)=X^H G_{\mathrm{b}}X-\lambda(X^H G_{\mathrm{w}}X-1)$ simultaneously reach their extreme values. Requiring the derivative of $L(X)$ with regard to X to be zero yields $G_{\mathrm{b}}X=\lambda G_{\mathrm{w}}X$. This implies that if we require $X^H G_{\mathrm{b}}X / X^H G_{\mathrm{w}}X$ to reach its extremes, the corresponding X must be the eigenvectors of Eq. (3). We also note that because $G_{\mathrm{b}}X=\lambda G_{\mathrm{w}}X$ means $X^H G_{\mathrm{b}}X =\lambda X^H G_{\mathrm{w}}X$, we have $X^H G_{\mathrm{b}}X / X^H G_{\mathrm{w}}X=\lambda$. Because the optimal X should correspond to the largest $X^H G_{\mathrm{b}}X / X^H G_{\mathrm{w}}X=\lambda$ and λ is indeed the eigenvalue of Eq. (3), we know that the optimal X should be the eigenvector corresponding to the largest eigenvalue of Eq. (3). Thus, the proof is complete.

Also according to the LDA methodology, we should take as needed t transforming axes the t eigenvectors corresponding to the first largest t eigenvalues. The following two properties also hold for Eq. (3). The first property is that G_{b} and G_{w} are both Hermitian matrices and the eigenvalues of Eq. (3) must be real numbers. The second property is that both G_{b} and G_{w} are positive semidefinite matrices. Indeed, using the defitions of G_{b} and G_{w}, we can easily demonstrate these two properties. For real-world applications, if G_{w} is positive definite, we can solve Eq. (3) directly. Once G_{w} is not positive definite, we can replace G_{w} with $G_{\mathrm{w}}+\mu I$, where μ is a small positive number and I is an identity complex matrix. We should point out that for the same patterns, because G_{b} and G_{w} have much smaller dimensions than the scatter matrices of LDA, the probability of G_{w} being singular is much lower than that of the within-class matrix being singular.

3.2 *Relationship between IBLDA and Matrix-LDA, Complex-LDA Techniques*

As stated in Section 2, IBLDA is proposed for feature extraction of complex matrices. IBLDA may be also viewed as a generalized form of the previous LDA-related techniques. If imaginary parts of the complex matrices denoting the patterns in IBLDA are null, IBLDA will be degraded and formally identical to the matrix LDA technique presented in Ref. 23. Thus, we may say that the matrix LDA technique is just a special form of IBLDA. On the other hand, while IBLDA is developed for directly extracting features from complex matrices, complex-LDA can perform feature extraction only for one-dimensional complex vectors, a class of special complex matrices. Thus, complex LDA in Ref. 22 can also be viewed as a special form of IBLDA. Hence, in this sense, IBLDA can be regarded as a unified framework of all the methods based on the LDA methodology.

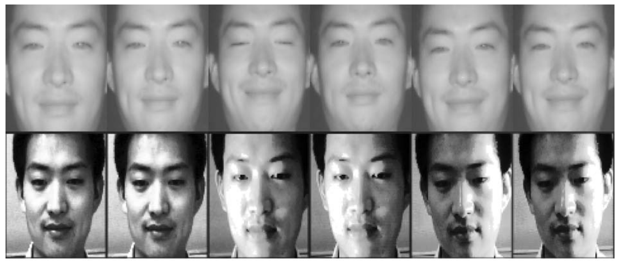

Fig. 1 Several near-infrared face images and visible-light face images of one subject from our face data set. (a) and (b) show the near-infrared and visible-light face images, respectively. The near-infrared and visible-light face images in (a) and (b) are all adopted with the environmental illumination. The near-infrared and visible-light face images in (c) and (d) are all adopted with the left illumination. (e) and (f) show the near-infrared and visible-light face images adopted with the right illumination.

4 Experimental Results

In this section, we perform identity identification experiments on one face data set, including visible-light and near-infrared face images, as well as one data set, including left ear and right ear images, respectively. These experiments will illustrate the performance difference between IBLDA and other discriminant analysis methods.

4.1 *Experiment on a Face Data Set Including Visible Light and Near-Infrared Face Images*

We construct a biometric data set including near-infrared and visible-light face images and also test our method using this data set. We have developed a low-resolution face verification system, which uses a CMOS PC camera to capture the visible-light face image and can verify the person's identity using the face image obtained. We exploit this system to captured 30 face images for each of 50 subjects. Among these visible-light images of each subject, 10 face images are captured in the condition of environmental illumination, another 10 face images are captured with the environmental illumination and the illumination from a lamp set on the left side of the subject (hereafter referred to as left illumination) and the other 10 face images are captured with the environmental illumination and the illumination from a lamp set on the right side of the subject, hereafter referred to as right illumination. We also captured 30 near-infrared face images for each subject in the same way. Figure 1 shows several near-infrared and visible-light face images of one subject.

We test IBLDA, TDDT using near-infrared face images (i.e., near-infrared TDDT), TDDT using visible-light face images (i.e., visible-lighting TDDT), matching score level fusion approach of near-infrared TDDT and visible-lighting TDDT (i.e., score fusion of TDDT), TDDT using the direct combination of near-infrared and visible-light face images (i.e., direct combination of TDDT), as well as complex LDA. Complex LDA first transforms each face image into a one-dimensional vector. Then complex LDA combines the two vectors of one visible-light face image and one near-infrared face image of a subject to form a one-dimensional complex vector and then performs feature extraction using the LDA methodology. Direct combination of TDDT works as follows: It first combines one $m \times n$ visible-light face image and one $m \times n$ near-infrared face image of a subject to form one $m \times 2n$ matrix and then exploits TDDT to perform feature extraction for this $m \times 2n$ matrix. All these methods belong to LDA methods.

We present the experimental results using Fig. 2, which shows that our method (IBLDA) can obtain the highest classification accuracy among all the methods. For example, the highest classification right rates of IBLDA, direct combination of TDDT, and score fusion of TDDT are 100, 94, and 98%, respectively. The experiment also shows that the combination use of low-resolution visible-light and near-infrared face images can obtain satisfactory recognition performance.

4.2 *Experiment on an Ear Data Set Including the Left and Right Ear Images*

We also test IBLDA and other methods using one ear data set constructed by us. This ear data set is made up of 12 ear images collected from each of 11 subjects for a total of 132 images. For each subject, six images are the images of his/her left ear and the others are images of the right ear. Figure 3 shows the six left ear images and the six right ear images of one subject from this data set. From Fig. 3, we know that there exist rotation variation and scale variation between

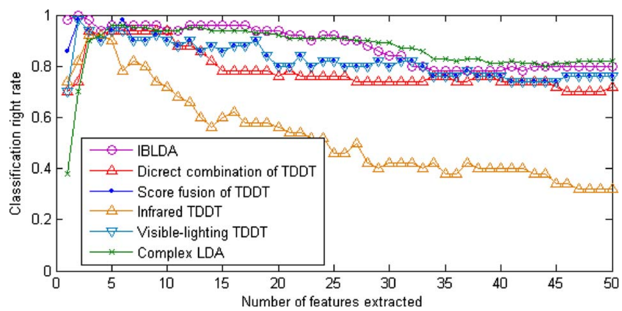

Fig. 2 Classification right rates of different methods on the face data set.

Fig. 3 (a) six left ear images and (b) six right ear images of one subject.

different images of the same subject. In addition to these variations, the existence of hair is also one of the factors that may affect the recognition result.

In this section, each of complex LDA, score fusion of TDDT, direct combination of TDDT, and IBLDA is implemented in the same way as its implementation in Section 4.1 except that it uses the ear images. Left TDDT and right TDDT denote the TDDT methods implemented for left ear images and right ear images, respectively. Figure 4 shows classification right rates of different methods on the ear image data set. From Fig. 4, we also see that IBLDA can obtain a higher classification right rate than other methods.

5 Conclusion

In this paper, we succeed in exploiting IBLDA to fuse two biometric images of TBIS at the feature level and to extract features from the fused biometric images. Compared to LDA, IBLDA can provide more accurate evaluation for the scatter matrix and is able to overcome the SSS problem and produce the nonsingular within-class scatter matrix. Moreover, the proposed method is very suited to feature extraction of the TBIS. As a feature level fusion method, IBLDA can also implement fusion of two biometric images in a simple and straightforward way at the feature extraction stage. The experiment result shows that IBLDA can outperform other LDA methods.

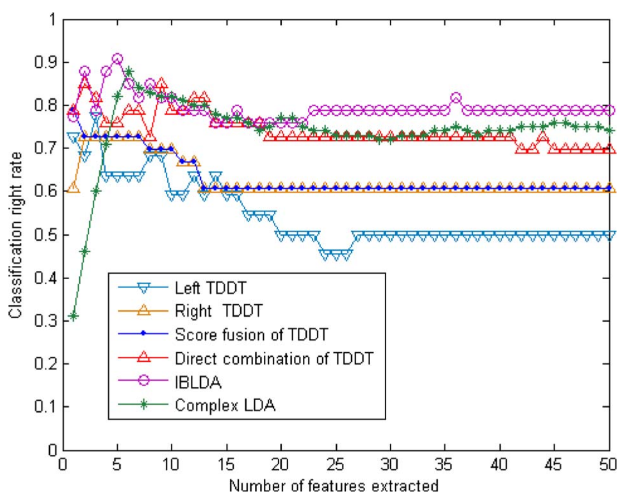

Fig. 4 Classification right rates of different methods on the ear image data set.

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