Bimodal biometrics based on a representation and recognition approach

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Abstract. It has been demonstrated that multibiometrics can produce higher accuracy than single biometrics. This is mainly because the use of multiple biometric traits of the subject enables more information to be used for identification or verification. In this paper, we focus on bimodal biometrics and propose a novel representation and recognition approach to bimodal biometrics. This approach first denotes the biometric trait sample by a complex vector. Then, it represents the test sample through the training samples and classifies the test sample as follows: let the test sample be expressed as a linear combination of all the training samples each being a complex vector. The proposed approach obtains the solution by solving a linear system. After evaluating the effect, in representing the test sample of each class, the approach classifies the test sample into the class that makes the greatest effect. The approach proposed is not only novel but also simple and computationally efficient. A large number of experiments show that our method can obtain promising results.© 2011 Society of Photo-Optical Instrumentation Engineers. [DOI: 10.1117/1.3554740]

Subject terms: biometrics; pattern recognition; computer vision; face recognition.

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1 Introduction

Biometrics, which focuses on identifying personal identities using static characters such as face, palmprint, fingerprint, or dynamic traits such as voice, signature of the individuals, is attracting increasing attention of the researchers in the areas of pattern recognition and computer vision.[1–3] It has been proved that the use of multimodal biometric traits of individuals can achieve a higher accuracy than the use of a single biometric.[4–12] The system that uses two biometric images to perform identity authentication is a special and simple form of the multimodal biometric system and is usually referred to as bimodal biometrics.[13] Actually, a bimodal biometric system can be viewed as the simplest multibiometric system.[2] It seems that this kind of system not only can fuse two distinct biometric traits such as the face and speech,[5] shape and texture,[6] face and fingerprint,[7] ear and face,[8] the fingerprint and the iris,[9] as well as hand and face,[10] but also can fuse two different but somewhat similar biometric traits such as the left palmprint and right palmprint image,[14] the visible light face image and the infrared face image,[15] as well as the left and right ear image.

A variety of schemes have been proposed for implementing multibiometrics including bimodal biometrics. It is commonly accepted that there are three main kinds of biometric fusion schemes,[2] i.e., the feature level fusion scheme,[10,13–17] the matching score level fusion scheme,[18–22] and the decision level fusion scheme.[23–25]

In this paper, we propose a novel feature level fusion approach to bimodal biometrics. This approach first denotes the biometric trait samples including the training and test samples by complex vectors. The approach assumes that the test sample can be expressed as a linear combination of all the training samples and obtains the solution by solving a linear system. After evaluating the effect in representing the test sample of each class, the approach classifies the test sample into the class that makes the greatest effect. We perform a large number of experiments to test our method. Experimental results show that our method can obtain a better classification performance than the state-of-the-art fusion approaches.

We note that some complex-vector-based methods such as complex PCA and complex LDA have been proposed.[16,26] Q2 The approach proposed in this paper is distinct from these methods in the following aspects: first, the methods in Refs. 16 and 26 are transform-based methods that transform samples and classify samples in a new space, whereas our method does not need any transforming. Second, the methods in Refs. 16 and 26 classify the test sample by calculating the distance or similarity between this sample and all the training samples. However, our method first computes the effect of each training sample in representing the test sample, and then classifies the test sample to the class that makes the greatest effect among all the classes. Our method not only provides a novel and feasible feature level fusion approach to bimodal biometrics, but also explores its potential.

We also note that the sparse representation method has been used for face recognition,[27–29] background modeling,,[30] clustering,,[31] motion segmentation,[32] image classification tasks,,[33] cancer biomarker identification,,[34] signal processing,[35,36] and gene selection.[37] We show that although the sparse representation method[27,28] is also derived from the idea of representing the test sample by using the training samples in the original space, it has several disadvantages. First, as the sparse representation method assumes that the sparse linear combination of the training samples, i.e., a linear combination of one subset of all the training samples, can well represent the test sample, and it has to obtain its solution at a high computational cost. Second, from

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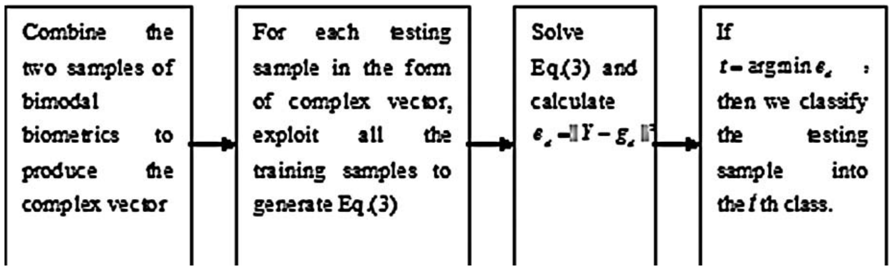

Fig. 1 The following block diagram of the main steps of our method.

the viewpoint of data representation, a certain linear combination of all the training samples can express the test sample more accurately than the sparse linear combination. Indeed, if the sparse linear combination is too sparse, the representation result will have a large deviation from the test sample, which probably causes bad classification performance. Third, since its solution is produced by an iterative linear programming algorithm, it seems that the solution might not be unique.

In our experiment, we compared our new method with popular PCA and LDA. All the methods are tested by only image data. We conducted the comparison on three biometric face databases. When implementing either PCA and LDA, we integrated the score level fusion[2] with them in order to perform bimodal biometrics. The experiment results show that our method performs better than PCA and LDA in face recognition accuracy.

The rest of the paper is organized as follows: Sec. 2 describes our method. Section 3 presents the experimental results and gives some analysis of them. Section 4 offers our conclusions.

2 Our Method to Represent the Test Sample

In this section we briefly describe our method. Suppose that there are L classes. Let $A_1 \ldots\ldots A_n$ denote n training samples of the first biometric trait in the original space. Let $B_1 \ldots\ldots B_n$ be n training samples of the second biometric trait in the original space. Suppose that all the samples, i.e., A_k and $B_k (k = 1, 2, \ldots, n)$, are in the form of column vectors. We can use $C_k = A_k + iB_k \; (k = 1, 2, \ldots, n)$ to stand for the k'th sample of the bimodal biometric trait. Hereafter, $C_k (k = 1, 2, \ldots, n)$ is referred to as a bimodal training sample. Let Y denote the test sample of the bimodal biometric trait. Y and C_k are all complex vectors.

We assume that in the original space test sample, Y can be represented by a linear combination of all the training samples, i.e.

$$Y = \sum_{k=1}^{n} \beta_k C_k. \tag{1}$$

Equation (1) can be rewritten into the following equation:

$$Y = C\beta, \tag{2}$$

where $\beta = (\beta_1 \ldots \beta_n)^T$, $C = (C_1 \ldots C_n)$.

We devise an objective function $Z = ||Y - C\beta||^2 + \gamma||\beta||^2$, where γ is a positive constant. We solve Eq. (2) under the constraint that Z should reach its minimum value. Using the Lagrangian algorithm, we have

$$\beta = (C^T C + \gamma I)^{-1} C^T Y, \tag{3}$$

where I is the identity matrix.

From Eq. (1), we know that every training sample makes its own effect in representing the test sample. The effect that the k'th training sample makes is $\beta_k C_k \; (k = 1, 2, \ldots, n)$. Since we know which class each training sample $C_k \, (k = 1, 2, \ldots, n)$ belongs to, we can calculate the sum of the effect of the training samples from each class. For example, if all the training samples from the d'th class are $C_s \ldots C_t$, then the effect in representing the test sample of the d'th class will be $g_d = \beta_s C_s + \cdots + \beta_t C_t$. We can covert g_d into a two-dimensional image and refer to it as the reconstruction images generated from the d'th class. We assume that the smaller the $e_d = ||Y - g_d||^2 \; (d = 1, 2, \ldots, L)$, the greater the effect of the dth class. We classify Y into the class that makes the greatest effect. The following block diagram clearly presents the main steps of our method (Fig. 1).

3 Experiments

We performed the experiments using three bimodal databases, i.e., CSIST, Lab1, and Lab2 face image databases. Both Lab1 and Lab2 face image databases were created by our lab, Bio-Computing Research Center. The common characteristic of the three databases is that each subject in the database simultaneously provides its visible light face images and near-infrared face images. Using these three databases, we conducted a series of experiments to test the performance of our new method, as well as two popular face recognition methods, PCA and LDA. The experiments of PCA or LDA were implemented as follows: we first applied PCA or LDA to visible light face images and near-infrared face images, respectively. As a sample had a visible light face image and a near-infrared face image, PCA or LDA produced two features for a sample, the feature of the visible light face image, and the feature of the near-infrared face image. We calculated the distances between the PCA-based or LDA-based feature extraction results of the test sample and training samples. For a test sample and a training sample, we first normalized the distance and then calculated the sum of the distance (referred to as summed distance) between the features of the visible light face images of these two samples and the distance between the features of the near-infrared face image of these two samples. We classified the test sample into the class of the training sample that had the minimum summed distance. Indeed, our experiments on PCA and LDA used the matching score level fusion scheme.[38] Hereafter, we refer to PCA and LDA as PCA score level fusion and LDA score level fusion, respectively.

In this section, we will first present experimental details including data preprocessing, the training set and test set, and the parameters of PCA and LDA. We then show the experimental results and provide the analysis of them.

Table 1 Average face recognition error rates of LDA score level fusion and our method on CSIST.

Algorithms	Average error rate
LDA (score level fusion)	9.42%
Our method	5.08%

3.1 *Experimental Detail*

3.1.1 *Data preprocessing*

Before implementing our method, we first performed some preprocessing steps for the face images. The images of the CSIST database and Lab2 database are all RGB color images. We first transformed the color images to gray images using the following linear transformation:

$$\text{Gray} = 0.299 \times R + 0.587 \times G + 0.114 \times B. \tag{4}$$

where Gray denotes the pixel value of the obtained gray images. The range of the pixel values generated from the color images is 0 to 255. We normalized all of the pixel values by dividing them by 255, so the range of the pixel values becomes 0 to 1.

It seems that the face image matrix has a large dimension. For example, the size of every face image of the CSIST database is 128×128. As a result, if we convert the image into a one-dimensional vector, its dimension will be 16,384. When we use the MATLAB software to implement PCA and LDA on this database, we always encounter the "out of memory" error. In order to overcome this problem, we first used the down-sampling algorithm in Ref. 39 to transform the original face image into a 64×64 image and then converted the obtained image into a one-dimensional vector. After obtaining the one-dimensional vector $\mathbf{x}$ of each face image, we converted it into a unit vector using the following equation:

$$\mathbf{x}' = \mathbf{x}/||\mathbf{x}||, \tag{5}$$

where $\mathbf{x}'$ represents the unit vector obtained and $\|\mathbf{x}\|$ is the norm of $\mathbf{x}$. We applied PCA, LDA, and our method to the one-dimensional unit vectors. We also dealt with the face images of Lab1 and Lab2 databases in the same way.

3.1.2 *Training set and test set*

We adopted different schemes to divide the images of a face database into a training set and a test set. For the CSIST and Lab1 databases, we performed experiments on all possible training sets and the corresponding test sets generated from the available images. If s samples of all the n samples of one class are used for training, there are $\binom{n}{s} = [n(n-1)\ldots(n-s+1)]/s(s-1)\ldots 1$ possible combinations that can divide the n samples into training and test samples. We used the same combinations to determine training samples and test samples for all the classes. Thus, there are $\binom{n}{s}$ training sets and corresponding $\binom{n}{s}$ test sets. Because the number of samples from per class in the Lab2 database is very large, we did not perform experiments for all the possible training and test sets.

Table 2 Average face recognition error rates of PCA score level fusion on CSIST.

Dimension of the features obtained using PCA	50	100	150	200
Average face recognition error rate	10.83%	9.42%	9.42%	9.42%

Fig. 2 The visible and near-infrared face images of one subject in the CSIST database. The first row shows the visible light face images and the second row shows the near-infrared face images.

3.1.3 *Experiment details of PCA and LDA*

PCA and LDA are two popular dimensionality reduction methods and have been used as baseline face recognition algorithms. PCA finds a low-dimensional embedding of the data points that best preserves their variance as measured in the high-dimensional input space.[40] The goal of LDA is to transform the samples into a new space where the ratio of between-class scatter matrix and within-class scatter matrix is maximized.

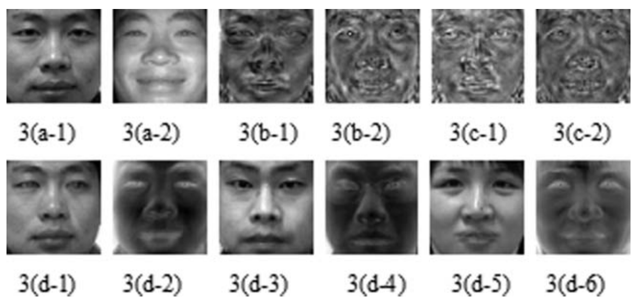

Fig. 3 Two original visible and near-infrared face images from the CSIST database and the images corresponding to the reconstruction results (referred to as reconstruction images) of these two images. a-1 and a-2 show the original visible and near-infrared face images. b-1 and b-2 show the reconstruction images, of the original visible and near-infrared face images, obtained using PCA. c-1 and c-2 show the reconstruction images, of the original visible and near-infrared face images obtained using LDA. d-1, d-2, d-3, d-4, d-5, and d-6 show the reconstruction images generated from the three classes that make the first three greatest effects in representing the test sample. d-1, d-3, and d-5 denote the reconstruction images of the real part of the complex sample vector, i.e., the original visible light face image, generated from the three classes that make the first three greatest effects in representing the test sample. d-2, d-4, and d-6 denote the reconstruction images of the imaginary part of the complex sample vector, i.e., the original near-infrared face image generated from the three classes that make the first three greatest effects in representing the test sample.

Table 3 Time taken by PCA score level fusion, LDA score level fusion, and our method on CSIST.

Algorithms	PCA score level fusion	LDA score level fusion	Our method
Time (seconds)	1809	2237	17

Let S_w and S_b denote the within-class matrix and between-class matrix in LDA, respectively. To prevent S_w from being singular, we regularize S_w by $S_w = S_w + \mu I$, where I is the identity matrix and μ is a small positive constant. We set $\mu = 0.001$ for all the experiments.

In the LDA algorithm, the maximum possible rank of S_b is $c-1$ where c is the number of classes. As a result, $(S_w + \mu I)^{-1} S_b$ has at most $c-1$ nonzero eigenvalues.[41,42] Because of this, we used LDA to transform the image data into a $c-1$ dimensional subspace. We also used PCA to transform the image data into 50, 100, 150, and 200 dimensional vectors, respectively.

3.2 *Experiment Result and Analysis*

In this section, we provide the experiment results of face recognition of PCA score level fusion, LDA score level fusion, our new method on the three bimodal databases, and give some simple analysis to them as well. When implementing our method, we set μ to 0.001. The personal computer used has the Intel(R) Core(TM)2 Quad CPU (Q8300 2.5G) and 2.0 G physical memories. The software used is MATLAB.

3.2.1 *Experiment result and analysis on the CSIST database*

The CSIST database contains one visible light face image database and the corresponding near-infrared face image database. Each of the two databases contains 400 face images from 100 subjects, each providing four images. We selected one visible light image and one near-infrared image from every subject as training samples and the left as test samples. We tested all the test sample sets as described in Sec. 3.1.2 and computed the average performance of them as the final result. Table 1 shows the average recognition error rates of LDA score level fusion and our method on the CSIST database. The number of training samples per subject is 1 and the dimension of the features obtained using LDA is 99. Table 2 shows the average face recognition error rates of PCA score level fusion on the CSIST database. Figure 2 shows the visible and near-infrared face images of one subject in the CSIST database. The first row shows the visible light face images and the second row shows the near-infrared face images. Figure 3 shows two original visible and near-infrared face images from the CSIST database and the images corresponding to the reconstruction results (referred to as reconstruction images) of these two images.

From Tables 1 and 2, we see that our method obtains a much lower error rate than PCA score level fusion and LDA score level fusion. The average face recognition error rate of our method is 4% lower than those of PCA score level fusion and LDA score level fusion. Table 3 shows the time taken by PCA score level fusion, LDA score level fusion, and our method. This table indicates that our method took much less time than PCA score level fusion and LDA score level fusion.

Table 4 Average face recognition error rates of LDA score level fusion and our method on Lab1.

TrainNo	2	3	4	5	6
LDA score level fusion	0.09%	0.01%	0	0	0
Our method	0.10%	0.01%	0	0	0

Table 5 Average face recognition error rates of PCA score level fusion on Lab1.

TrainNo/ Dimension of the features	2	3	4	5	6
50	0.41%	0.26%	0.19%	0.13%	0.09%
100	0.41%	0.27%	0.19%	0.13%	0.09%
150	0.41%	0.27%	0.18%	0.13%	0.09%
200	0.41%	0.27%	0.18%	0.13%	0.09%

3.2.2 *Experiment result and analysis on the Lab1 database*

The Lab1 database also simultaneously contains visible light images and near-infrared images of the subjects. There are 500 visible light face images and 500 near-infrared face images from 50 subjects, each providing 10 visible and near-infrared images. These images were acquired under strictly constrained conditions. The size of every face image is 100×80 and we resized them to 50×40. We simultaneously selected 2, 3, 4, 5, and 6 visible light images and near-infrared images, respectively, from every subject as training samples and took the remainder as test samples. We conducted experiments for all the possible training sets and test sets and show the average recognition error rates. Table 4 shows the average recognition error rates of LDA score level fusion and our method on the Lab1 database, where "TrainNo" denotes the number of training samples per subject. The dimension of the features obtained using LDA is 49. Table 5 shows average face recognition error rates of PCA score level fusion on Lab1 database.

On the Lab1 database, the average face recognition error rates of PCA score level fusion, LDA score level fusion, and our method are all lower than 1%. Moreover, when the number of training samples per subject is greater than or equal to 4, the error rates of these methods are near zero. Tables 4 and 5 show that our method performs better than PCA score level fusion. Table 6 shows the time taken by PCA

Table 6 Time taken by PCA score level fusion, LDA score level fusion, and our method on Lab1.

Algorithms	PCA score level fusion	LDA score level fusion	Our method
Time (seconds)	186	320	5

Fig. 4 Some visible and near-infrared face images of the first two subjects in the Lab2 database. The first and second rows show some visible light face images and near-infrared face images of the first subject, obtained under varying illuminations. The third and fourth rows show some visible light face images and near-infrared face images, of the second subject, obtained under varying illuminations.

score level fusion, LDA score level fusion, and our method in the case where the first two samples of each subject were used as training samples, and the remaining samples were used as test samples. We can conclude that our method is computationally much more efficient than PCA score level fusion and LDA score level fusion.

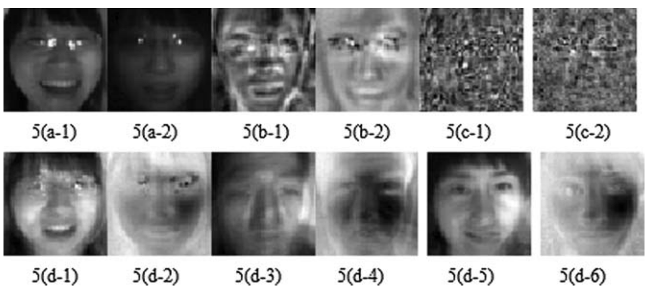

Fig. 5 Two original visible and near-infrared face images from the Lab2 database and the images corresponding to the reconstruction results (referred to as reconstruction images) of these two images. a-1 and a-2 show the original visible and near-infrared face images.. b-1 and b-2 show the reconstruction images of the original visible and near-infrared face images, obtained using PCA. c-1 and c-2 show the reconstruction images of the original visible and near-infrared face images, obtained using LDA. d-1, d-2, d-3, d-4, d-5, and d-6 show the reconstruction images generated from the three classes that make the first three greatest effect in representing the test sample. d-1, d-3, and d-5 denote the reconstruction images of the real part of the complex sample vector, i.e., the original visible light face image, generated from the three classes that make the first three greatest effect in representing the test sample. d-2, d-4, and d-6 denote the reconstruction images of the imaginary part of the complex sample vector, i.e., the original near-infrared face image generated from the three classes that make the first three greatest effects in representing the test sample.

Table 7 Face recognition error rates of LDA score level fusion and our method on Lab2.

Method	Recognition error rate
LDA score level fusion	30.20%
Our method	23.20%

3.2.3 *Experimental result and analysis on the Lab2 database*

The Lab2 database also simultaneously contains visible light images and near-infrared images of the subjects. This database contains 1000 face images from 50 subjects, each providing 20 images. These images were acquired under the following four different illumination conditions: a. under the environment illumination (referred to as "normal") condition, b. under the condition of the environment illumination pulse the illumination of the left incandescent lamp (referred to as "left"), c. under the condition of the environment illumination pulse the illumination of the right incandescent lamp (referred to as "right"), d. under the condition of the environment illumination pulse the illumination of the left and the right incandescent lamps (referred to as "both"). The size of every face image is 200×200 and we resized all of them to 50×50 images. We selected the images with both and left illuminations as training samples and the others as test samples. Figure 4 shows some visible and near-infrared face images of the first two subjects in the Lab2 database. Figure 5 shows two original visible and near-infrared face images from the Lab2 database and the images corresponding to the reconstruction results (referred to as reconstruction images) of these two images.

Table 7 shows the recognition error rates of LDA score level fusion and our method on the Lab2 database. The dimension of the features obtained using LDA is 49. Table 8 shows the recognition error rates of PCA score level fusion. We see that our method obtains a much lower error rate than LDA score level fusion and PCA score level fusion. Table 9 shows that our method also took less time than PCA score level fusion and LDA score level fusion.

3.3 *Experiment Conclusion*

From the experiment results on the CSIST, Lab1, and Lab2 databases, we see that our method out-performs PCA score level fusion and LDA score level fusion. In addition, on all of the three databases, our method always runs much faster than PCA score level fusion and LDA score level fusion. Our method also has the following potential advantages. First, our method fuses visible and near-infrared face images at

Table 8 Face recognition error rates of PCA score level fusion on Lab2.

Dimension of the features obtained using PCA	50	100	150	200
Face recognition error rate	49.20%	48.00%	48.40%	48.00%

Table 9 Time taken by PCA score level fusion, LDA score level fusion and our method on Lab2.

Algorithms	PCA score level fusion	LDA score level fusion	Our method
Time(seconds)	370	581	26

the feature level, which can convey the richest information of the bimodal biometric traits among all the possible fusion schemes. Second, the solution of our method can be obtained at a so low computational cost that its implementation is much faster than PCA score level fusion and LDA score level fusion.

4 Conclusion

Our method is not only a novel approach to bimodal biometrics, it also has the following characteristics: first, it proposes for the first time, to represent the bimodal test sample as a linear combination of the bimodal training samples. Second, it devises a very simple and reasonable algorithm to classify the test sample. This algorithm first evaluates the power of representing the test sample of the bimodal training samples from a class, and then it classifies the test sample into the class that has the maximum power. Our method also provides an interesting and very useful feature level fusion approach to bimodal biometrics.

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Biographies and photographs of the authors not available.

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