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Research Article

Face Recognition Incorporating Ancillary Information

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Due to vast variations of extrinsic and intrinsic imaging conditions, face recognition remained to be a challenging computer vision problem even today. This is particularly true when the passive imaging approach is considered for robust applications. To advance existing recognition systems for face, numerous techniques and methods have been proposed to overcome the almost inevitable performance degradation due to external factors such as pose, expression, occlusion, and illumination. In particular, the recent part-based method has provided noticeable room for verification performance improvement based on the localized features which have good tolerance to variation of external conditions. The part-based method, however, does not really stretch the performance without incorporation of global information from the holistic method. In view of the need to fuse the local information and the global information in an adaptive manner for reliable recognition, in this paper we investigate whether such external factors can be explicitly estimated and be used to boost the verification performance during fusion of the holistic and part-based methods. Our empirical evaluations show noticeable performance improvement adopting the proposed method.

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1. INTRODUCTION

Over the past few decades, face recognition has emerged to be among the most active and challenging research problems in computer vision and image analysis. Particularly, the subspace projection-based face representation techniques such as PCA [1], LDA [2], ICA [3], and LFA [4] have achieved remarkable progress in terms of recognition performance. However, the performance of current systems is still limited by external conditions such as illumination, head pose, facial expression, and occlusion [5–8].

A lot of research efforts have been spent to overcome the deteriorating effects of these external factors. Particularly, the part-based face representation methods, such as independent component analysis (ICA) and local feature analysis (LFA), have shown promising performance under certain facial conditions. As the performance of projection-based methods (such as PCA) relies heavily on accurate face normalization, the sensitivity to normalization inherently imposes the requirement of good image quality. The part-based methods relax much of this image quality constraint. The advantage of these part-based methods over the projection-based methods comes from their spatially localized basis vectors. Since face is a nonrigid object, these part-based face representations are less sensitive to facial variations due to partial occlusions and local distortions.

However, the part-based method alone loses the global relationship information among various face features. As such, holistic methods, such as PCA, still show better performance for minor distorted face images as in simple duplications or images with slight facial expressions than that of the part-based method. Based on this viewpoint, it has been argued that practical systems should adopt a combination of global and local part-based methods to stretch the overall system's verification performance [4, 5]. This point of view is also encouraged by those studies on human nature in psychology community which insists that people should utilize both local and global features of faces for recognition [9].

To realize this paradigm, an efficient fusion strategy is needed. There have been much research efforts set forth to fuse the local and global information in score level [10]. Sum-rule fusion, voting fusion, or other classifiers such as support vector machines (SVM) have been adopted for the score-level fusion. However, most fusion strategies seek to locate a fixed set of weights between both pieces of information. This is quite different from the behavior of human cognition where the global features have been utilized for recognizing a remote face and the local features have been utilized to recognize an occluded face such as one wearing sunglasses. This shows that fusion of the holistic and the part-based methods should be adaptive to external conditions of the input face image.

In this paper, we propose a method to isolate the external factors for efficient fusion of holistic (global) and part-based (local) information. We will investigate whether the external factors can be explicitly estimated and be used to boost the verification performance or not. Essentially, the problem is treated as an estimation and classification problem. Encoding and estimation schemes are proposed to handle the complex situations whereby individual external *factor* (such as pose, illumination, expression, and occlusion) contains varying *conditions* (such as directions of illumination and pose, and location of occlusion). A classification framework is then employed to deal with these multiple external factors and face features. Empirical experiments were performed to observe the effectiveness of the proposed method using the AR database [11].

The rest of this paper is organized as follows. In Section 2, the proposed methodology is described and illustrated. Essentially, a coding system is formulated to provide an explicit descriptor of the external conditions. The estimated codes which represented the environmental information are subsequently fused with local and global face feature information for identity verification. In Section 3, the database and the details of our experimental observations are presented. Finally, some concluding remarks are drawn in Section 4.

2. PROPOSED METHODOLOGY

2.1. Dealing with external factors

2.1.1. Segregating different factors using code words

We present a fundamental strategy to deal with external factors in this section. The basic idea is to encode the various external factors so that these codes can be utilized to segregate the different factors where an adaptive fusion of all information for verification can be performed. Similar to normalization techniques, we can anticipate that good verification performance will be achieved whereby the identities from face images can be easier distinguished or matched under homogenous conditions than that under a flood of different external factors which make the appearance different even for the same identity.

This method is motivated by our experimental observation. Figure 1 shows an exemplary case. Each dot in this figure represents the measured face similarities between a probe and a gallery in terms of the PCA output space (i.e., Euclidean distance from comparison of two points in PCA subspace which corresponds to the horizontal axis of plots in Figure 1) and the ICA output space (i.e., Euclidean distance from comparison of two points in ICA subspace which corresponds to the vertical axis of plots in Figure 1). Since each dot contains two (or more, for more than two modalities) distance components, we will call it a *face distance vector*. The grey tone and the dark tone dots denote the face distance vectors from genuine and imposter matches, respectively. According to the prior information regarding whether the subject in each image is wearing glasses or not, every match can be divided into two cases as shown on the right side of Figure 1: the top panel indicates that only one subject in either the probe image or the gallery image is wearing glasses, and the bottom panel indicates that either both objects are wearing glasses or both are not. It can be seen from this figure that the distributions of genuine and imposter distance vectors are more separable when they are divided than when they are mixed together. Hence, when a certain amount of prior information regarding the glasses of the subject is known, we postulate that a higher verification performance can be achieved by introducing two distinct classifiers for the two better segregated cases than that attempting to classify the mixed case using a single classifier.

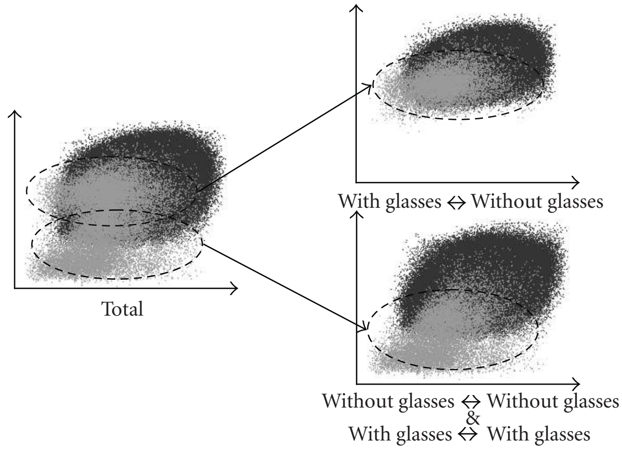


Figure 1: Distribution of genuine (grey tone) and imposter (dark tone) face distance vectors.

Apart from the information on wearing glasses, the above matching data (distance vectors) can be extended to various cases using information from other external factors such as illumination, pose, and facial expression. Although the data distribution of a case of external factor is different from that of another case, the information on the external factors is homogenous within each case. Hence, a group of matching data under a single case can be treated as a *band*. In order to effectively separate the genuine and the imposter distributions in a manner similar to that in Figure 1, a local classifier is required for each pair of conditions within and between the bands. Since the entire combinatorial pairs within and between the external factors should be considered, this will result in an explosion of the number of local classifiers required.

Here, we devise a solution which integrates multiple local classifiers into a single classification framework. Firstly, we define an axis, which we called a *code distance axis* (this terminology will be explained in greater detail in next section) in addition to the axes of the face distance vector. With this definition of a new axis, we can then assign a certain coordinate value to each band, and we will call this value a *code distance*. The code distance of one band should be different from another band indicating difference among those

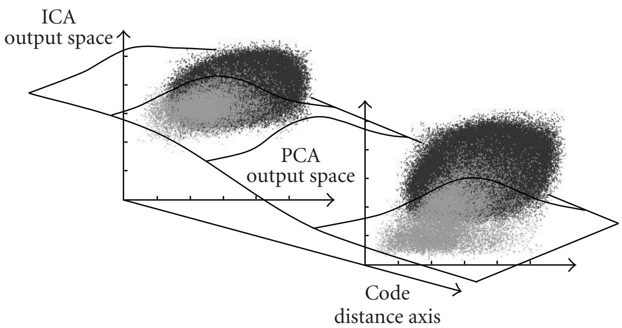


Figure 2: Separating hyperplanes in a newly defined higher-dimensional space (here, e.g., three dimensions). The black curved lines represent the decision hyperplanes ordered according to different code distances.

external factors. As illustrated in Figure 2, the mass of data can be divided into different bands in the space along the code distance axis when all the various external factors are considered. Since the code distance axis can cater for various external factors, a single classifier can thus be designed to fuse the diverse information within a single classification framework. Here, we note that the prior information regarding external factors is unknown in real-word applications, and it has to be estimated. An estimation-classifier will be designed for individual external factor estimation and a fusion-classifier will be designed for information fusion after estimation. We will employ the well-known SVM classifier for both external factors estimation and information fusion, and pay particular attention to illumination variations, facial expressions, and partial occlusions in this study.

2.1.2. Code design

As mentioned above, in order to sort and segregate the entire set of face distance vectors according to the external variables, a new axis is defined. This code distance axis needs to satisfy the following two conditions for effective information segregation. Firstly, the coordinates within the code distance axis should vary according to the difference among the external factors. This is obvious, because the objective of this new axis is to separate each band such that a large difference between two external factors results in a large matching error. Secondly, within each band, the symmetry between external factors of the probe and the gallery should be satisfied. This is because the objective of a verification system is merely to measure the similarity between two input face images regardless of whether it is probe or gallery. Hence, a matching data should remain within the same band when the external factors of its probe and gallery are reversed.

Considering these requirements, we decided to represent each external condition with appropriate code words, such that each matching coordinate (from comparison of two code words) along the code distance axis is determined by the Euclidean distance between the code words of probe and gallery. This is the main reason that the new axis is called a code distance axis. In the rest of this section, we will discuss the design of our code word system.

We begin with an intuitive code assignment which assigns a 2-digit binary code for the illumination condition according to the lighting sources. There are four different illumination conditions in AR database namely, interior light (IL) where the subject is illuminated only by the interior lights, left light (LL) where an additional light source on the left is turned on, right light (RL) where an additional light source on the right is turned on, and bidirectional light (BL) where additional light sources on the left and on the right are both turned on. Here, the following codes are assigned: $\{0, 0\}$ for IL, $\{1, 0\}$ for LL, $\{0, 1\}$ for RL, and $\{1, 1\}$ for BL. Although this intuitive encoding appears to give a clear representation of external conditions, it causes problems which eventually degrade the recognition performance. These problems are enumerated as follows.

Firstly, the integer value encoding causes an overlap of different bands which should have been separated. In other words, there exist different bands which share the same code distance. For example, the code distance between IL and LL and that between LL and BL are both equal to 1, while the actual distributions of these two bands are quite different from each other.

Secondly, this method cannot guarantee appropriate ordering of data distribution along the code distance axis. Let us give an example using the illumination factor. Consider a band where IL images and RL images are matched within, and another band where IL images and BL images are matched within (for convenience sake, we will call them IL-RL band and IL-BL band, resp.). Since the BL (bidirectionally illuminated) face images are more uniformly illuminated than the RL faces images, the contrasting effect is less severe for IL-BL than that for IL-RL. Consequently, the desired threshold of the IL-BL band should be smaller than that of the IL-RL band. However, the computed code distances are $\sqrt{2}\,(= \|[0\ 0] - [1\ 1]\|)$ and $1\,(= \|[0\ 0] - [0\ 1]\|)$, respectively for IL-BL and IL-RL. This shows the ordering effect of code distance with respect to amount of difference among the conditional pairs.

Figure 3 illustrates this ordering problem with simplified examples. Here, the genuine and the imposter matches are plotted on coordinates according to their image distances (e.g., PCA, ICA, or LFA output space) and code distances. Unlike Figures 1 and 2, this figure shows only one face feature with code distance for simplicity. From Figure 3(a), which illustrates the match data distribution according to the intuitive code design, it follows that the trained separating hyperplane would be too curvy and the margin could be very narrow due to the unordered distributions. For such case, it would be difficult for SVM to converge to a separating hyperplane which generalizes well.

In order to circumvent the above problems, we assign floating point numbers for code words and define a code distance axis for each of the modalities being fused to reflect the distributions of corresponding data groups under conditional variations. Here, we establish a principle of designing code word in which the code distance varies according to the mean of the distribution of corresponding genuine-user matched distances of each modality from training data. Satisfying this principle, we postulate that the coded data would

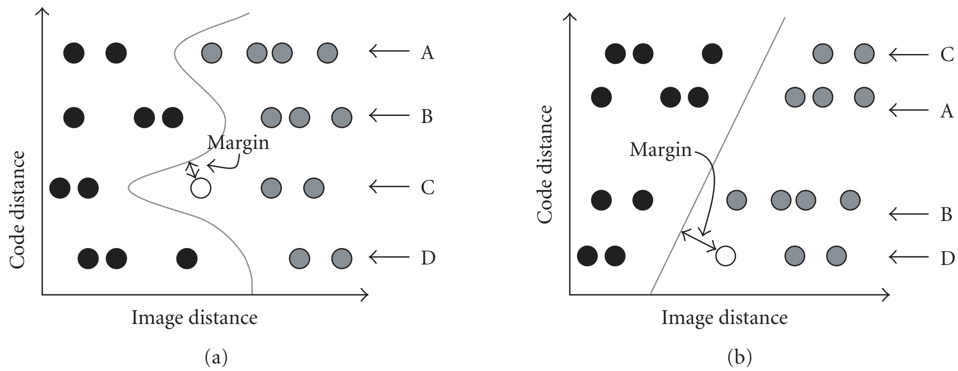


Figure 3: Variation of match distributions: the black and the grey circles denote the genuine and the imposter matches, respectively, and the white circle denotes a new sample match. The grey line between the circles indicates an optimal separating hyperplane of SVM. (a) Intuitive code design leads to a curvy optimal separating hyperplane and narrow margin. (b) Our final code design leads to an almost straight hyperplane and wider magin.

then be distributed as illustrated in Figure 3(b), where we obtain a nearly straight separating hyperplane and wide margin.

According to the above principle of code design based on the mean of genuine-user distance distribution, the following procedure is established to compute an ordered set of vertices which reveals the intrarelationship among the step differences within each external factor (e.g., for the external factor on illumination, those left, right, frontal, and bidirectional illumination step differences should occupy vertices which show connections among each other as seen in Figure 4).

(1) Order the conditions within the external factor from 1 to n, where n is the total number of the conditions (e.g., illumination: 1. frontal, 2. left, 3. right, and 4. bidirectional lighting).
(2) Find the entire combinatorial set of code distances from the available face distances. Each of the code distances is computed based on the mean of genuine-user face distances of corresponding band which matches images from ith condition with images from jth condition $D_{i,j}$ $(0 \leq i < j \leq n)$.
(3) Assign an $n-1$ dimensional zero vector to the first of the ordered conditions as its code.
(4) Initialize the code of the next (say kth) condition as $C_k = [c_k^1 c_k^2 \cdots c_k^{k-1} 0 \cdots 0]$. Then calculate C_k from the solution of the following simultaneous equations:

$$\begin{gathered} \|C_1 - C_k\| = D_{1,k}, \\ \|C_2 - C_k\| = D_{2,k}, \\ \vdots \\ \|C_{k-1} - C_k\| = D_{k-1,k}. \end{gathered} \tag{1}$$

(5) Repeat procedure 4 until the nth condition.

We will walk through an example of encoding the PCA feature based on the four conditions within the illumination factor (for fusion of multiple modalities, this procedure should be repeated for those other modalities to be fused with PCA in order to find their code words). From the four kinds of known illumination conditions, the geometric relationship among the codes of illumination is the shape of a tetrahedron as shown in Figure 4. The bits length of the code word for illumination would be at least 3 since the tetrahedron is of 3-dimensional shape. The only prerequisite condition for the code word design is the distances among code words for different conditions where these distances should reveal the relationships among the conditions. In other words, we care only about the shape of the tetrahedron (lengths of its 6 edges) in Figure 4, and we do not care about its absolute position or rotation in the three-dimensional code word space.

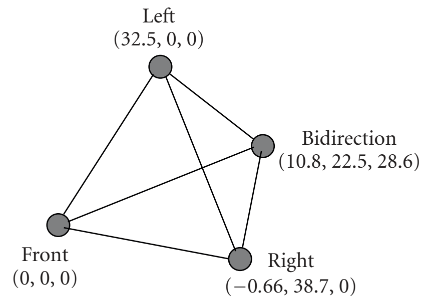


Figure 4: An example code assignment for illumination.

Starting with IL (interior light), we assign a code word $C_{\text{IL}} = \{0, 0, 0\}$ for IL. Then we calculate the code distance between the codes of IL and LL (left light), $D_{\text{IL,LL}}$ by taking the average of face distances of genuine-user matchings when the illumination conditions of their galleries are IL and those of their probes are LL. Now, we can calculate the code of LL, $C_{\text{LL}} = \{c_{\text{LL}}^1, c_{\text{LL}}^2, c_{\text{LL}}^3\}$, using the equation $(\|C_{\text{IL}} - C_{\text{LL}}\|)^2 = (D_{\text{IL,LL}})^2$. Here, we arbitrarily initialize the code of LL as $C_{\text{LL}} = \{c_{\text{LL}}^1, 0, 0\}$ wherein c_{LL}^2 and c_{LL}^3 are set to zeros because C_{LL} can be any point when the distance from C_{IL} satisfies $D_{\text{IL,LL}}$. From our experimental data, $D_{\text{IL,LL}}$ is found to be 32.5, and hence the resulting C_{LL} is $\{32.5, 0, 0\}$. In a similar manner, we can find the code for RL (right light) C_{RL} using $D_{\text{IL,RL}}$, $D_{\text{LL,RL}}$, C_{IL}, and C_{LL}. Also, the code for BL (bidirectional light) C_{BL} can be calculated. This procedure can be

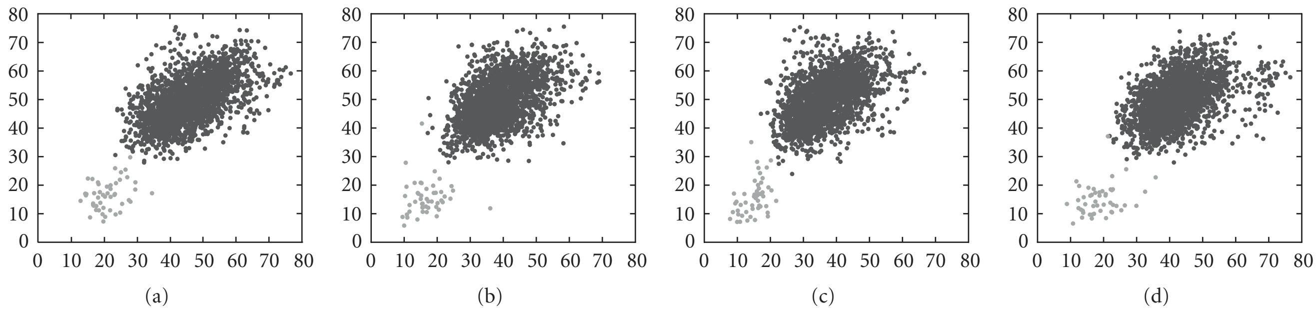


FIGURE 5: Face distance vector distribution comparing smiling faces with frowning faces under different illuminations. (x-axis is PCA output space, y-axis is ICA output space.) The illumination conditions of probe and gallery are (a) interior light, (b) left light, (c) right light, and (d) bidirectional lights.

summarized as solving the following second-order simultaneous equations:

(i) initialization: $C_{\mathrm{IL}} = \{0, 0, 0\}$ $C_{\mathrm{LL}} = \{c^1_{\mathrm{LL}}, 0, 0\}$ $C_{\mathrm{RL}} = \{c^1_{\mathrm{RL}}, c^2_{\mathrm{RL}}, 0\}$ $C_{\mathrm{BL}} = \{c^1_{\mathrm{BL}}, c^2_{\mathrm{BL}}, c^3_{\mathrm{BL}}\}$,

(ii) simultaneous code distance equations (six combinations from the four conditions):

$$\begin{aligned}
(\|C_{\mathrm{IL}} - C_{\mathrm{LL}}\|)^2 &= (D_{\mathrm{IL,LL}})^2,\\
(\|C_{\mathrm{IL}} - C_{\mathrm{RL}}\|)^2 &= (D_{\mathrm{IL,RL}})^2,\\
(\|C_{\mathrm{LL}} - C_{\mathrm{RL}}\|)^2 &= (D_{\mathrm{LL,RL}})^2,\\
(\|C_{\mathrm{IL}} - C_{\mathrm{BL}}\|)^2 &= (D_{\mathrm{IL,BL}})^2,\\
(\|C_{\mathrm{LL}} - C_{\mathrm{BL}}\|)^2 &= (D_{\mathrm{LL,BL}})^2,\\
(\|C_{\mathrm{RL}} - C_{\mathrm{BL}}\|)^2 &= (D_{\mathrm{RL,BL}})^2,
\end{aligned} \tag{2}$$

(iii) the resulting code words for illumination conditions are shown in Figure 4.

Theoretically, when we design the code word by the above method, we have to consider the entire set of all possible combinations of conditions among the external factors of the database. However, excessively long code words would then be required and we have to solve complex simultaneous equations. Instead, we assume that each kind of external factor affects the face distances independently. This assumption is justifiable from our empirical observations as shown in Figure 5. The four plots in Figure 5 show the distribution of face distance vectors (in PCA and ICA output spaces) from a comparison of images of smiling face with images of frowning face. The difference among these plots is the illumination condition of both probe and gallery images. The illumination condition for both the probe and the gallery is IL in Figure 5(a), LL in Figure 5(b), RL in Figure 5(c), and BL in Figure 5(d). Here we find that the distribution of face distances between images of two different expressions is quite similar regardless of the illumination condition. Hence, we can postulate that facial expressions and illuminations are nearly independent in terms of their resultant matching effects. Based on this observation and assumption, we then consider each external factor separately. For illumination, as mentioned, since there are four kinds of illumination conditions in our database, we assigned 3 digits. Our final code design has 3 digits for expression, 1 digit for sunglasses, and 1 digit for scarf, all according to the available experimented conditions from AR database. The total eight code words are organized as shown in Figure 6. Finally, we consolidate the code words for each factor and build a mapping table which is filled with these code words.

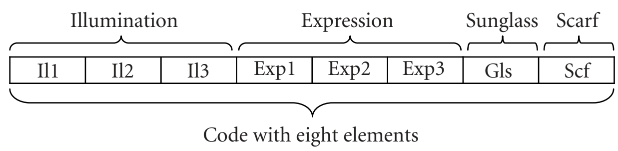


FIGURE 6: The organization of total eight code words.

2.1.3. *Estimation of external factors*

Thus far, we have discussed combining the face similarity information and external factor information with the assumption that we already know the external factors of each image. However, in real-life applications, no prior knowledge about the external factors is provided, and an estimation of the external conditions is essential in order to implement this method. To estimate the external conditions, we adopted the training-based approach. In [12], Huang et al. reported excellent pose estimation result in their work and this inspired us to estimate the external conditions by extending their SVM-based approach. An SVM (we called it code-estimation-SVM which is differentiated from the classification or fusion-SVM for identity verification) is deployed to learn and then estimate the external conditions for unseen data.

The PCA feature was used as the main input of these code-estimation-SVMs since it has high sensitivity to the external factors. As a result, the PCA feature will always be used for code estimation, no matter what face representation method is being encoded. As shown in Figure 7, the PCA coefficients of the face images were fed into the SVMs which have been trained under different conditions. Four distinct multiclass SVMs were trained to estimate the conditions of each external factor from the AR database. Based on the estimated information, we encoded the final external conditions

Table 1: Condition code mapping for each method.

Condition	(symbol : label)	PCA code	ICA code	LFA code
Illumination	Interior (IL : 1)	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)
	Left (LL : 2)	(32.5, 0, 0)	(1.21, 0, 0)	(0.72, 0, 0)
	Right (RL : 3)	(−0.66, 38.7, 0)	(0.21, 1.31, 0)	(0.33, 0.67, 0)
	Bidirection (BL : 4)	(10.8, 22.5, 28.6)	(0.55, 0.67, 0.98)	(0.42, 0.36, 0.61)
Expression	Neutral (NE : 1)	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)
	Smile (SE : 2)	(26.3, 0, 0)	(1.03, 0, 0)	(0.67, 0, 0)
	Anger (AE : 3)	(2.89, 26.1, 0)	(0.24, 1.13, 0)	(0.16, 0.75, 0)
	Scream (SE : 4)	(12.8, 23.9, 24.3)	(0.49, 0.89, 0.98)	(0.31, 0.62, 0.65)
Sunglasses	Without (NG : 0)	0	0	0
	With (WG :1)	41.1	16.3	1.39
Scarf	Without (NS : 0)	0	0	0
	With (WS : 1)	51.1	15.1	1.92

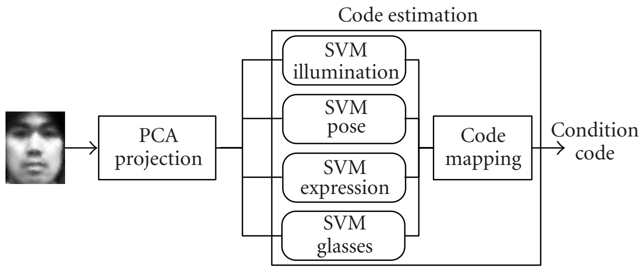


Figure 7: The process of code estimation.

by mapping the code words from a code mapping table. Since the code words provide information about distribution of the face distances of a given modality, the code words of the mapping table should be obtained based on the face representation method which is being encoded. In other words, even when the ICA face feature is combined with its code (coded-ICA), the estimation-SVM still takes PCA coefficients as its input, except that the code mapping table is determined by ICA features (an example of the code mapping table is shown in Table 1).

2.2. Information fusion

With the main idea of the proposed method, in this section we will specify the entire system flow. Two different scenarios will be considered: the first is to combine different facial information of a single face feature (either PCA, ICA, or LFA) with its corresponding code information; and the second is to combine all information including the global (PCA), the local (ICA or LFA), and their corresponding code information. Through these two scenarios, we can empirically verify the advantages of our system in terms of performance enhancement in aspects of isolation of effects of external factors and fusion efficiency. We will call the first a coded-feature (e.g., either coded-PCA, coded-ICA, and coded-LFA) and call the second a coded-fusion system.

2.2.1. *Coded-feature: combining face data and condition codes*

As described in the previous section, the information from external factors estimation will be fused with the face information using SVM (fusion-SVM). Given a probe image, its environmental/conditional factors are first estimated and encoded by the estimation-SVM which takes the PCA coefficients of the image. The code distance is calculated by comparing the estimated code of the probe image with that of the gallery image. The face distance is next computed in a similar way by comparing the face templates from the probe and the gallery. Eventually the feature vector, which consists of the code distance and the face distance, is fed into the SVM classifier which decides whether the probe is a genuine-user or an imposter. Figure 8(a) shows a system which combines the code output distance and the original feature output distance from, for example, the ICA feature.

2.2.2. *Coded-fusion: fusion of coded global and local face features*

We will work on both the holistic (PCA) and part-based (either ICA or LFA) feature extraction methods in this study. Apart from the conditional code, both holistic and part-based face features are important direct information for identity discrimination. Thus, fusion of all these data will widen the between-class variation at the higher dimensional space.

Combining two face features with the codes is a rather straightforward procedure. For each and every probe and gallery match, we feed the face distances and the code distances into the fusion-SVM directly. Figure 8(b) shows an entire system fusing PCA and ICA feature distances with estimated conditional code distances. The output of the fusion-SVM is a score indicating whether the matching belongs to a genuine-user match or an imposter match. Certainly, apart from combining PCA with ICA features, other features such as LFA can also be incorporated into the system in Figure 8(b) by replacing the position of ICA to extend the recognition capability.

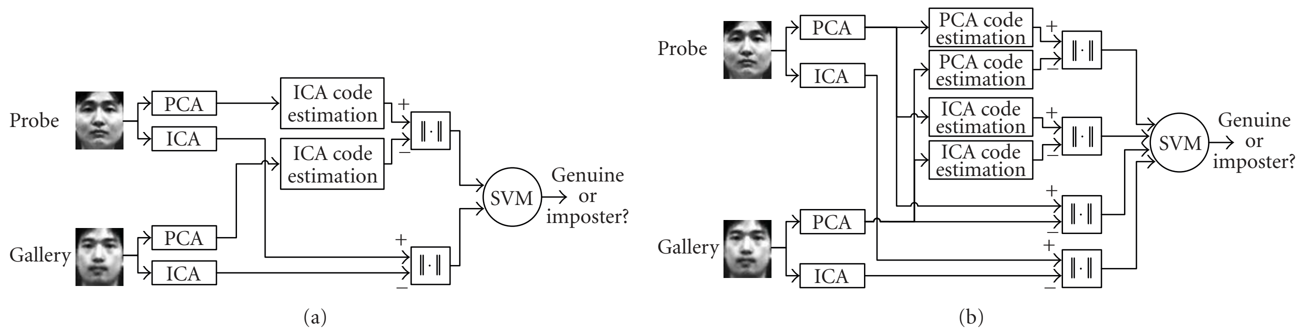


FIGURE 8: Diagram for (a) coded-ICA and (b) coded-fusion.

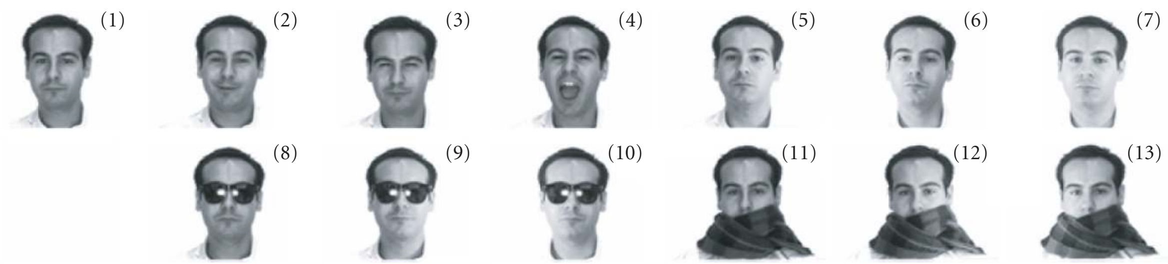


FIGURE 9: The conditions of AR database: (1) neutral, (2) smile, (3) anger, (4) scream, (5) left light on, (6) right light on, (7) both lights on, (8) sunglasses, (9) sunglasses/left light, (10) sunglasses/right light, (11) scarf, (12) scarf/left light, (13) scarf/right light.

3. EXPERIMENTS

3.1. *Data set: AR database*

To evaluate the proposed method, we adopted a publicly available database, the AR database from [11]. The AR database contains 3315 images from 116 individuals. Each person participated in two sessions (some of them only participated in one session), which are separated by a two-week time interval. For each session, 13 images were captured under different states by varying illumination, facial expression, and occlusion using sunglasses and scarf. Figure 9 shows a sample set of 13 images from one session. The face of each image was located manually by clicking a mouse at the center of each eye. All images were normalized to 56×46 pixels according to the eye centers, by rotating and subsampling. Then, the images were histogram-equalized, and the pixels were normalized to have zero mean and unit variations. The training set and the test set are not composed to have any common person, for example the training set consists of images of people whose ID number is odd and the test set consists of the remaining images.

3.2. *Experimental design*

In this section, we explain the specifications regarding our experiments. All the experiments were performed under the identity verification scenario. Utilizing all images from the AR database, the sizes of genuine-user and imposter populations generated for verification are, respectively, 20 124 and 1 363 492 for training and 20 046 and 1 342 029 for test. For each face feature extraction method, we used different number of features which shows the best verification performance (for PCA, 275 features were used; for ICA, 225 features were used; and for LFA, 20 features were used). The receiver operating characteristic (ROC) curve and the equal error rate (EER) will be used to compare the performances.

3.2.1. *Condition code estimation*

Our first experiment is to observe the accuracy of condition code estimation. The code estimator is composed of two parts: the first part is to estimate the external condition of an input image (condition estimator), and the second part is to map proper code words based on the estimated external conditions (code mapping table). The condition estimator takes the PCA features of the input image and then outputs a label indicating the external condition of the input. We first labeled each of training images based on the ground truth of external conditions. For example, image (9) of Figure 9 is labeled as 2-1-1-0 (illumination-expression-sunglasses-scarf) which means that the subject is illuminated by left light, with neutral expression, wearing sunglasses, and wearing no scarf. Then, we trained the condition estimators using these labels and PCA coefficients of the training set. A total of four SVMs were trained to estimate illumination, pose, expression, and glasses, respectively.

Unlike the condition estimators, the code mapping part is determined based on the adopted face feature. This means that for coded-ICA, the code words should be determined based on means of ICA projected data. For coded-LFA, the code words should be determined based on means of LFA data, and for coded-PCA, the code words should be

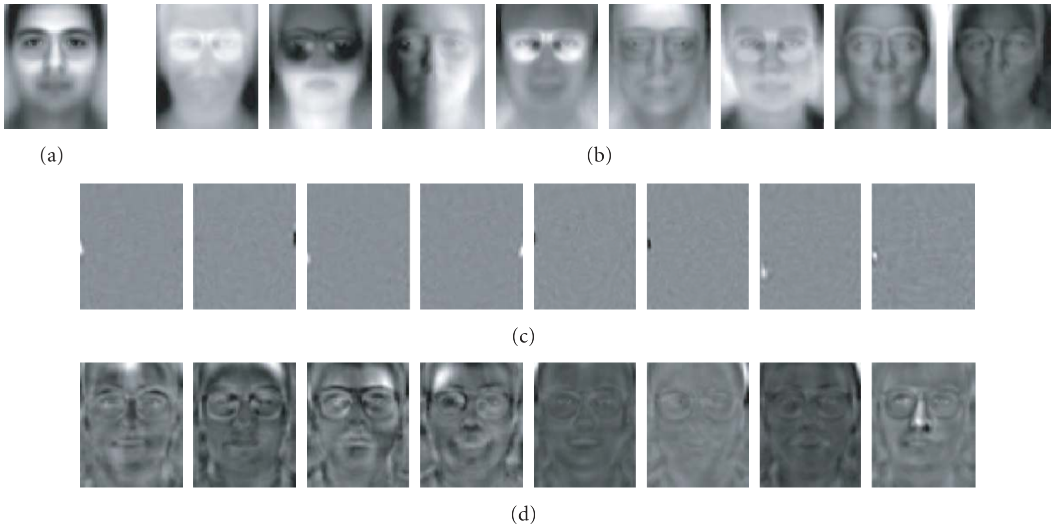


Figure 10: (a) Mean images; (b) leading PCA bases; (c) leading ICA bases; (d) leading LFA bases.

Table 2: Composition of AR database subsets for experiment 2.

Subset names	Included image numbers of AR database
Illumination variation	{1, 5, 6, 7}
Expression variation	{1, 2, 3, 4}
Sunglasses variation	{1, 8}
Scarf variation	{1, 11}

Table 3: Results of code estimation.

Condition	Estimation accuracy (%)
Illumination	99.33
Expression	94.37
Sunglasses	100.00
Scarf	99.94

determined based on means of PCA data. Figure 10 shows the mean vector and leading basis images of each face representation method. To summarize, using the projected data, we obtain the face distances of all possible genuine-user matches within each of the training set. Then, using the distribution of these face distances, we build the code mapping table for each method following the procedure in section 2.2.1. The resulting code mapping table is shown in Table 1.

Putting the condition estimators and the code mapping table together, we then complete the code estimation process. The process of the code estimator for coded LFA, for example, is as follows. Firstly, the PCA coefficients of a given input image are fed into the condition estimators. Assume that the estimated result is 4-1-0-1. Then the corresponding code word for the external factor is picked: $\{(0.42, 0.36, 0.61)\ (0,0,0)\ (1.39)\ (0)\}$. Finally, these code words are concatenated in a code word $\{0.42, 0.36, 0.61, 0., 0, 0, 1.39, 0\}$ for the given input image. With the estimated code word, the accuracy of code estimation is finally computed by comparing it with the ground truth from the test set.

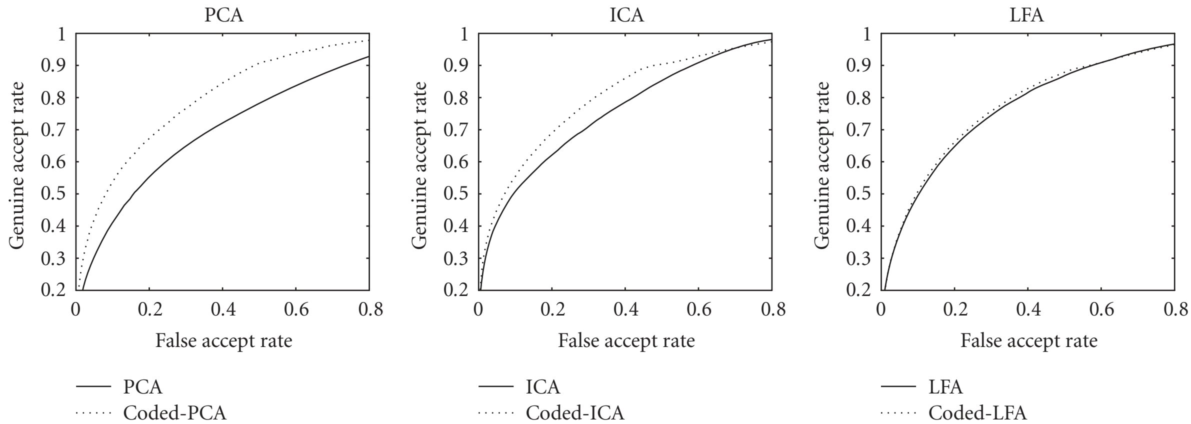
3.2.2. Fusion of single face feature with condition code

In the next experiment, we integrate our encoding scheme to each face feature (individually for PCA, ICA, and LFA). Our purpose is to validate whether the proposed method can isolate the effects of external factors and to observe which face feature can incorporate the encoding scheme more effectively. Using the projected feature data, we obtain the face distances of all possible matches within each of the training and the test set. Each of these distances is labeled as either a "genuine-user" or an "imposter" according to the known comparisons. Based on the ground truth of conditions from the training data set, we encoded the external conditions using the codes from the code mapping table. Then, we calculated the code distances of the training data set in a similar way to that we did for face distances.

Eventually, we have the face distances and the code distances computed for feeding into fusion-SVM for identity verification. We trained the fusion-SVM using these face and code distances obtained from the training data set. These inputs for the SVM were in the form of two-dimensional vectors and labeled as 0 or 1 according to whether they are from the genuine or the imposter matching. For test, the code words of the probe and the gallery are estimated by the code estimator, and their code distance is fed into fusion-SVM with corresponding face distance. Finally, the fusion-SVM outputs a value predicting whether they are genuine match (close to 0) or imposter match (close to 1).

3.2.3. Fusion of coded-PCA with part-based features

In this experiment, we test the proposed method for fusing the holistic and the part-based methods (coded PCA+ICA or coded PCA+LFA). Here we employ a similar code assignment as described in the previous section. The fusion-SVM



(a) (b) (c)

Figure 11: Test results of experiment 1 in ROC curves. The horizontal and the vertical axes indicate FAR (false accept rate) and GAR (genuine accept rate), respectively: (a) PCA and coded-PCA, (b) ICA and coded-ICA, (c) LFA and coded-LFA.

Table 4: Results of experiments.

Experiment	Methods	EER (%)
Coded-feature	PCA	32.76
	Coded-PCA	26.45
	ICA	29.48
	Coded-ICA	25.50
	LFA	27.62
	Coded-LFA	26.84
Coded-fusion	PCA+ICA	28.83
	Coded-PCA+ICA	24.94
	PCA+LFA	26.14
	Coded-PCA+LFA	21.25

takes the face distances and the code distances of each of both methods being fused as inputs in the form of a four-dimensional feature vector. For performance comparison purpose, we performed an additional experiment on simple fusion without inclusion of conditional codes.

Several subsets of test data as well as an entire one were experimented, in order to compare the performance of proposed method with that of PCA [1], ICA [3], and LFA [4] under variations of different external factors. The subsets are composed so that only one kind of external factor is varied within each subset. Those images which are included in each subset are tabulated in Table 2, and the labels of images are indicated in Figure 9.

3.3. Results

Condition code estimation

Table 3 shows the accuracy of code estimation using PCA coefficients test data. The estimation accuracy is the percentage of correctly estimated external condition with respect to the ground truth for the entire test set. It is seen here that for all external factors, the estimation rates are quite high. This result shows that the PCA coefficients contain rich information of external factors which can be useful for identity discrimination.

Fusion of condition code with single face feature

The resulting verification performances of the coded-feature experiments are shown in the form of ROC curves in Figure 11, and the corresponding EERs are shown in Table 4. Here we see that by applying the proposed method, we could improve the verification performances of all three face representations from the original PCA [1], ICA [3], and LFA [4]. These results show that the proposed method successfully isolates the effects of external factors. Particularly, the best improvement margin has been achieved using PCA features. On the other hand, there is only 1% of performance improvement from coded-LFA over LFA. This shows that PCA contains much information on external factors in addition to those identity discriminative features.

Fusion of coded-PCA with part-based features

The results from the final set of experiments are shown in Figure 12 and Table 5. Here, we achieved respectively 3.89% and 4.89% of performance improvements using coded-PCA+ICA and coded-PCA+LFA with respect to their corresponding simple-fusion. These results are seen to be higher than any of those singly coded-PCA, -ICA, and –LFA, hence suggesting the efficiency of our method for multiple features fusion. The experimental results on data subsets are also shown in Table 5. Among PCA, ICA, and LFA, the best method for each subset is different, but coded-PCA+ICA and coded-PCA+LFA outperform others for every external factor variation. These results reflect the adaptation of coded-method to various external conditions.

From Table 5, we can see that both PCA [1] and ICA [3] by themselves are severely weak for scarf variation. However, with coded-PCA+ICA, the situation improves significantly in this scenario of scarf variation. As for sunglasses

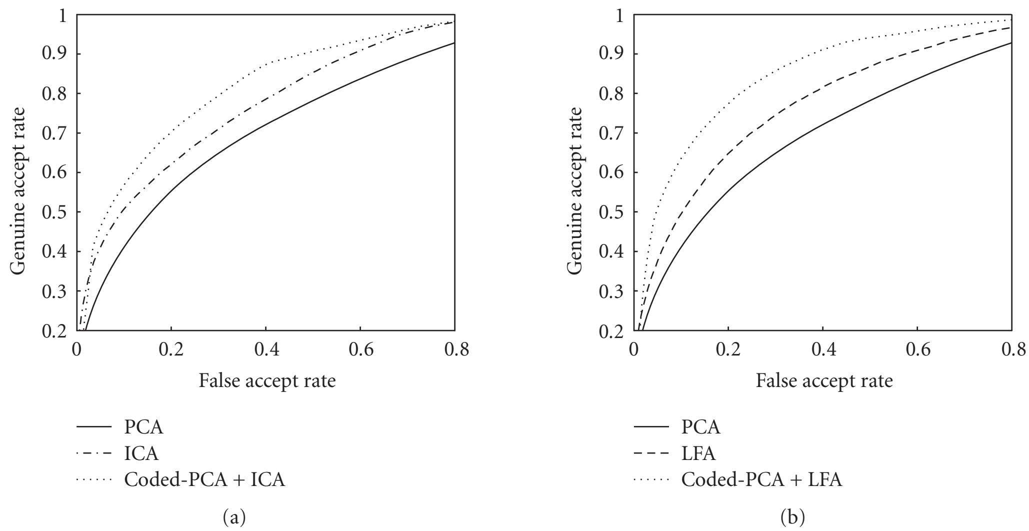


Figure 12: Test results of experiment 2 in ROC curves: (a) PCA, ICA, and coded-PCA+ICA, (b) PCA, LFA, and coded-PCA+LFA.

Table 5: Results of experiment on subsets of AR database in terms of EER.

Method	Total	Data subset			
		Illumination variation	Expression variation	Sunglasses variation	Scarf variation
Coded-(PCA+ICA)	24.94	13.02	**12.00**	17.26	29.24
Coded-(PCA+LFA)	21.25	**11.32**	12.29	**16.43**	**21.32**
PCA [1]	32.76	21.45	12.67	21.40	42.38
ICA [3]	29.48	15.82	14.68	20.30	39.58
LFA [4]	27.62	16.40	20.76	29.01	25.88

and other variations, the coded-PCA+ICA show consistent improvements over the relatively good verification performances. When comparing coded-PCA+LFA with the original LFA [4], similar improvements are seen for all external factor variations. These results support our claim that the proposed method isolates the effect of external factors.

4. CONCLUSION

In this paper, we proposed a code-based method which isolates the effects of external conditions from the feature data for effective identity verification. Main attention was paid to a robust classification scheme under considerable variation of environmental conditions. With deliberate design of a conditional code scheme, the code information was shown to aid the SVM to improve the verification performance than one without the code. Our empirical results show that the conditional code significantly contributes to SVM classification under a wide range of varying external conditions.

One major technical contribution of this paper is the introduction of a novel approach to deal with data variation in pattern recognition. In this application on face verification, we attempted to quantify the original cause of data variation and included these quantitative values for robust verification.

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