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Full Length Research Paper

Dynamic weighted discrimination power analysis: A novel approach for face and palmprint recognition in DCT domain

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Although Discrete Cosine Transform (DCT) is widely employed to extract proper features for biometric recognition, the problem on how to select proper DCT coefficients to obtain the best discrimination effect has not been solved satisfactorily. Some approaches discard the low-frequency DCT coefficients unreasonably and rely on proper premasking window to improve performance. But there is not a uniform criterion to optimize the shape and size of the premasking window, so it is an inconvenient processing for coefficient selection. Three processes, used to enhance discriminant ability in DCT domain, and the relationship between them are summarized and discussed systematically. Furthermore, this paper explains the phenomenon why the recognition rate is low without discarding the low-frequency DCT coefficients reasonably and then proposes dynamic weighted discrimination power analysis (DWDPA) to enhance the discrimination power (DP) of the selected DCT coefficients. DWDPA does not need premasking window and preserves more DCT coefficients with higher DP. Normalization prevents the DCT coefficients with large absolute values from destroying the DP of the other DCT coefficients that have less absolute values but high DP values. The DCT coefficients with larger DP values are given larger weights adaptively to optimize and enhance the recognition performance. The experiments on ORL, Yale and PolyU databases captured by biometric sensors prove the advantages of DWDPA obviously.

Key words: Dynamic weighted discrimination power analysis (DWDPA), discrete cosine transforms (DCT), biometric sensors, face recognition, palmprint recognition.

INTRODUCTION

Discrete Cosine Transform (DCT) is one of the most popular linear projection techniques for feature extraction like principal components analysis (PCA) and linear discriminant analysis (LDA) (Rao and Noushath, 2010). The favorable properties of DCT are summarized as follows:

(1) DCT is appropriate for removing statistical correlation and image compression because it is an orthogonal transform. The DCT components are similar to the principal components extracted by PCA which is based on K-L transform theory. The superiority of DCT to PCA is that DCT can be realized in a single image or signal, while PCA depends mainly on training samples.
(2) DCT can be realized by fast Fourier transform (FFT), while K-L transform has no fast realization algorithm at present.
(3) Frequency bands with favorable linear separability can be precisely selected appropriately.
(4) DCT coefficients are all real numbers, so the

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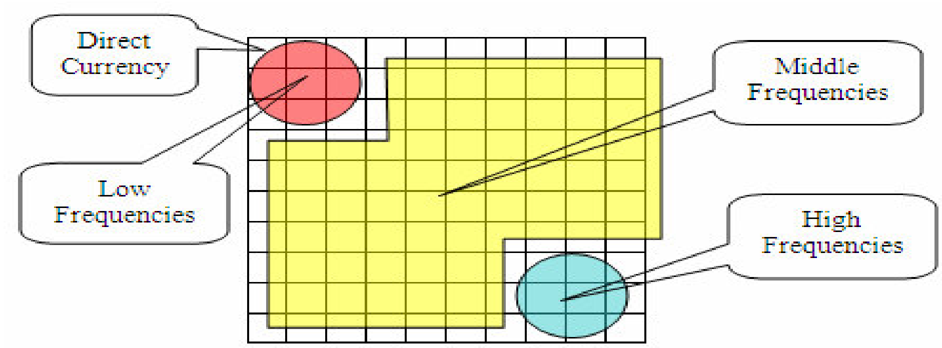

Figure 1. Frequency distribution of DCT.

frequency bands are easily and directly selected. In contrast, the results after Fourier transform (FT) are complex numbers. In order to evaluate the linear separability of frequency bands of FT, it is needed to evaluate interesting bands in the space-domain by inverse FT. The computational cost is large.
(5) DCT is a widely used technique in many standards of image coding and compression, like JPEG2000, MPEG, etc. Thus it is easy to be applied and realized in a great deal of occasion (Delac et al., 2009).

Due to its favorable properties, DCT has been employed successfully in many recognition problems of biometric captured (Khan, 2009) by biometric sensors, such as face recognition (Dabbaghchian et al., 2010; Podilchuk and Zhang, 1996), palmprint recognition (Jing and Zhang, 2004; Dale et al., 2009) and so forth. Some researchers fused DCT and other proper features to improve the recognition performance (Jadhav and Holambe, 2010; Liu and Liu, 2010; Nanni and Lumini, 2009). PCA and LDA can be directly implemented in DCT domain (Chen et al., 2005), so DCT is often combined with subspace method to enhance recognition accuracy (Dabbaghchian et al., 2010; Jing and Zhang, 2004; Samir et al., 2009). In addition, the security and privacy of biometrics is another significant realm. Some researchers have proposed schemes to protect biometric templates in transform domain (Khan et al., 2010).

Three processes can be used to enhance recognition ability in DCT domain, namely:

(1) Premasking: Frequency distribution of DCT is shown in Figure 1. A DCT coefficients matrix can be divided into three typical parts, namely low, middle and high frequencies. The premise of premasking is that not all DCT coefficients are effective. The DCT coefficients in red region of the up-left corner are low frequencies resulted from illumination, so low-frequency coefficients should be discarded in order to resist illumination variations. The DCT coefficients in blue region are high frequencies resulting from noise deteriorating discrimination power (DP), so high-frequency coefficients should also be discarded. The DCT coefficients in yellow region are middle frequencies.

Some approaches discard some DCT coefficients in low and high frequencies directly. The direct currency or the three DCT coefficients at the up-left corner are discarded in (Er et al., 2005) as shown in Figure 2(a). But there is not a uniform criterion to determine that how many coefficients should be discarded. Another premasking window in (Dabbaghchian et al., 2010) is shown in Figure 2(b). The DCT coefficients in white region of the up-left corner are low frequencies. The DCT coefficients in gray region are middle frequencies. The DCT coefficients in the remaining white region are high frequencies. But there is not a uniform criterion to determine the position of r_s, r_e, c_s and c_e (start row, end row, start column, end column) of the premasking window.

In fact, it is arbitrary to discard the low-frequency coefficients with high DP values. The performance of premasking template relies mainly on the specific circumstances of different databases. The reasons and more discussions are explained intensively in the following section.

(2) Coefficient selection: After discarding some useless coefficients in low and high frequencies, the amount of rest coefficients is also large, so it is necessary to select effective coefficients according to some order. Zigzag and zonal maskings are two conventional methods to select DCT coefficients by the scanning sequence shown in Figure 3(a) and (b) respectively. Besides, Jing and Zhang (2004) proposed an approach that first used a two-dimensional (2-D) separability judgment that can facilitate the coefficient selection of useful DCT frequency bands for image recognition. The basis of the approach is that not all the bands are useful in classification. The DCT frequency bands are selected according to their DP values. The theoretical threshold value of DP values is 1. But the threshold is not always optimal in different databases. As shown in Figure 3(c), the third, fifth and sixth bands are selected by Jing's approach. The approach is not proper to select helpful DCT

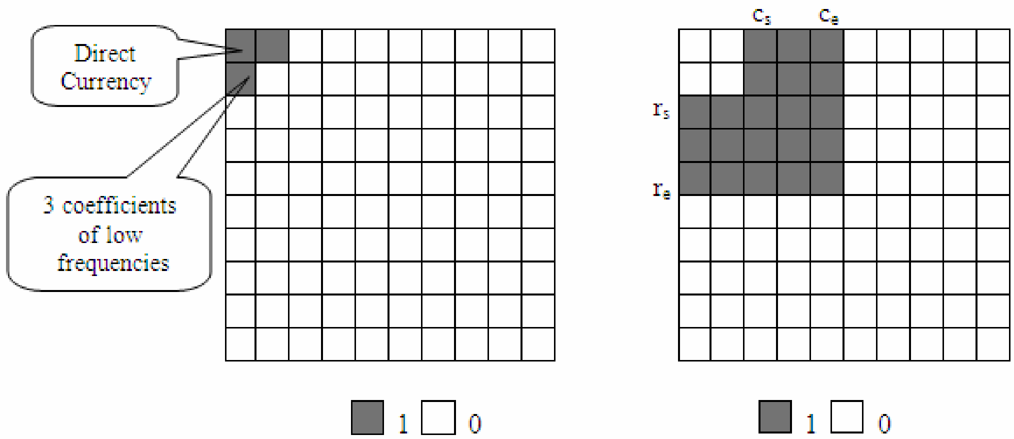

Figure 2. Premasking window of DCT coefficients. (a) Discard one or three coefficient(s) (b) Discard low and high frequencies.

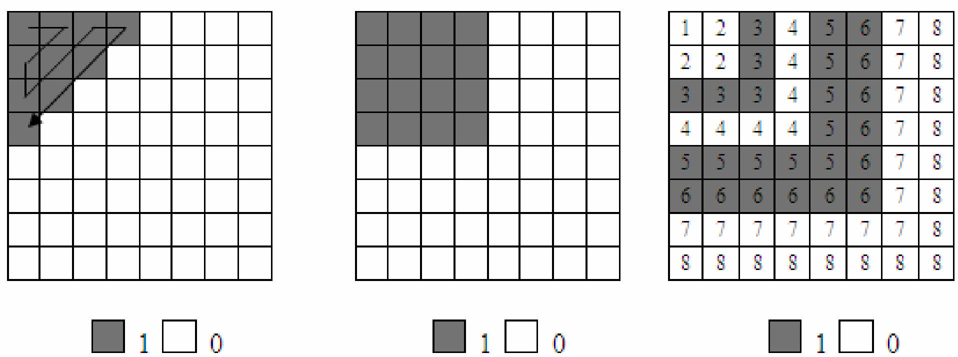

Figure 3. DCT coefficients selection (a) zigzag mask (b) zonal mask (c) Jing's bands.

coefficients and discard useless DCT coefficients as many as possible. According to Jing's criterion, some DCT coefficients have great DP values but occur in the frequency bands whose DP values are little, hence they would not be selected. However some DCT coefficients have little DP values but occur in the frequency bands whose DP values are great, and they will be selected.

There are also some other optimization algorithms, e.g. boosting and genetic algorithm (GA) based approaches, are used for the coefficient selection (Amine et al., 2008; Liu and Wang, 2008; Qing and Jiang, 2010), but they do not solve the weighted adjustment of DCT coefficient, in other words, they do not play the role of DP enough. Furthermore, the computational cost of optimization algorithms is large.

(3) **Weighted adjustment:** DCT coefficients play different role and effect in recognition. How to give the DCT coefficients weights according to a certain criterion to obtain better recognition ability is also a problem not settled satisfactorily. Random subspace method was applied for feature weighting (Nanni and Lumini, 2008). The features are multiplied by a weight factor to minimize the error rate in the training set. Particle swarm optimization was used to find the weights for each feature in each subspace. The main drawback, similar to GA, is that the computational cost is large. Histogram equalization was employed to stretch the contrast of the original images in order to resist illumination variance; and then the DCT coefficients in low frequencies were divided by a constant (Vishwakarma et al., 2007). The constant was set to 50 and the direct currency of DCT was increased by 10% to compensate contrast. The constant value was stable, so it cannot adapt to different databases. 10% is also not an optimized value. Another approach used for improving the performance after the feature extraction is to use a supervised feature transform (Franco et al., 2006).

The above three processes are shown in Figure 4. The three processes are optional, not necessary. We can select one process to enhance recognition ability; we can also combine two or three processes to improve

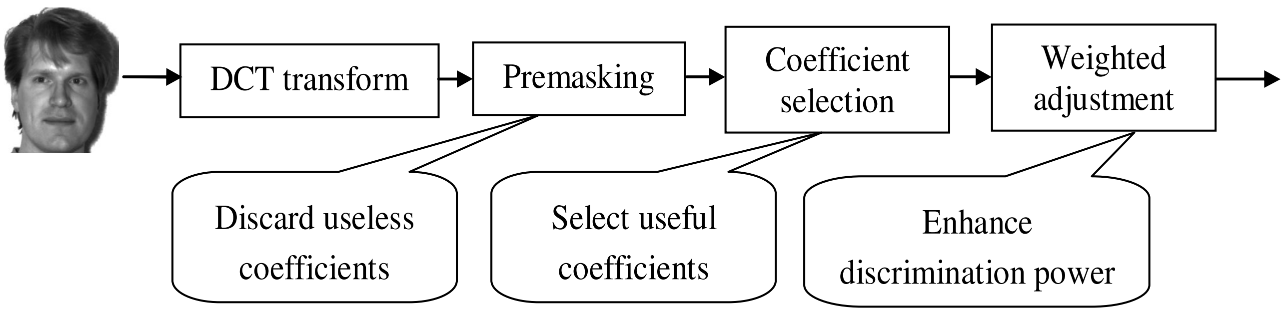

Figure 4. Three processes to enhance recognition ability in DCT domain.

recognition accuracy. The relationships between two processes or among three processes should be discussed and analyzed. The existing methods seldom consider the three processes in the round. So the objective of this paper is to analyze the three processes more deeply and systematically. Moreover the computational complexity of optimization algorithm is great, thus it is necessary to propose a simple and fast scheme with low computational cost.

Discrimination power analysis (DPA) is effective to select the feature coefficients that have more DP according to their separability through statistical analysis. A novel modified DPA, namely dynamic weighted DPA (DWDPA), is proposed to enhance the DP of the selected DCT coefficients. DWDPA does not need premasking window, in other words, it does not need to optimize the shape and size of premasking window. The DCT coefficients are adaptively selected according to their DP values. More DCT coefficients with higher DP are preserved. The selected DCT coefficients by their DP values are normalized and dynamic weighted according to their DP values. Normalization ensures that the DCT coefficients with large absolute value do not destroy the DP of the other DCT coefficients that have less absolute value but high DP values. Dynamic weighting gives larger weights to the DCT coefficients with larger DP values. The scheme optimizes and enhances the recognition performance by the above process. The experimental results show the superiority of DWDPA obviously.

Dynamic weighted discrimination power analysis

DCT

Suppose that an original image is sized $M\times N$ and expressed by $f(x,y)$, where $1\le x\le M$, $1\le y\le N$ and $N\le M$. (2D)DCT could be expressed as Equation 1.

$$F(u,v)=\alpha_u\alpha_v\sum_{x=1}^{M}\sum_{y=1}^{N}f(x,y)\cos\frac{(2x-1)u\pi}{2M}\cos\frac{(2y-1)v\pi}{2N} \tag{1}$$

where $1\le u\le M$, $1\le v\le N$ and $N\le M$.

$$\alpha_u=\begin{cases}1/\sqrt{M}, & u=1\\ \sqrt{2/M}, & 2\le u\le M\end{cases}$$

$$\alpha_v=\begin{cases}1/\sqrt{N}, & v=1\\ \sqrt{2/N}, & 2\le v\le N\end{cases} \tag{2}$$

$F(u,v)$ is the DCT coefficients matrix of $f(x,y)$. Obviously, $F(u,v)$ has the same size of $f(x,y)$.

DPA

DP of a coefficient depends on two attributes: the variation between the classes and the variation within the classes. Large DP has large variation between the classes and small variation within the classes. So DP can be estimated by the ratio of the between-class variance to the within-class variance. The high DP value means high discrimination ability. Equation 3 denotes the DCT coefficients matrix for an image size of $M\times N$.

$$X=\begin{bmatrix}x_{11} & x_{12} & \cdots & x_{1N}\\ x_{21} & x_{22} & \cdots & x_{2N}\\ \vdots & \vdots & \vdots & \vdots\\ x_{M1} & x_{M2} & \cdots & x_{MN}\end{bmatrix}_{M\times N} \tag{3}$$

The database has C classes and S training images for each class, totally $C\times S$ training images are presented. DP of each coefficient x_{ij} (i=1,2,…,M, j=1,2,…,N) can be estimated as follows:

(1) Construct the train set matrix A_{ij} by choosing the DCT coefficients of the positions i and j for all classes and all training images:

$$A_{ij} = \begin{bmatrix} x_{ij}(1,1) & x_{ij}(1,2) & \cdots & x_{ij}(1,C) \\ x_{ij}(2,1) & x_{ij}(2,2) & \cdots & x_{ij}(2,C) \\ \vdots & \vdots & \vdots & \vdots \\ x_{ij}(S,1) & x_{ij}(S,2) & \cdots & x_{ij}(S,C) \end{bmatrix}_{S\times C} \tag{4}$$

(2) Calculate the average value of each class:

$$M_{ij}^{c} = \frac{1}{S}\sum_{s=1}^{S} A_{ij}(s,c),\ c = 1,2,...,C \tag{5}$$

(3) Calculate variance of each class:

$$V_{ij}^{c} = \sum_{s=1}^{S}(A_{ij}(s,c) - M_{ij}^{c})^2,\ c = 1,2,...,C \tag{6}$$

(4) Average the variance of all the classes:

$$V_{ij}^{W} = \frac{1}{C}\sum_{c=1}^{C} V_{ij}^{c} \tag{7}$$

(5) Calculate the average of all training samples:

$$M_{ij} = \frac{1}{S\times C}\sum_{c=1}^{C}\sum_{s=1}^{S} A_{ij}(s,c) \tag{8}$$

(6) Calculate the variance of all training samples:

$$V_{ij}^{B} = \sum_{c=1}^{C}\sum_{s=1}^{S}(A_{ij}(s,c) - M_{ij})^2 \tag{9}$$

(7) Estimate the DP on location (i,j):

$$D(i,j) = \frac{V_{ij}^{B}}{V_{ij}^{W}},\ 1\le i\le M, 1\le j\le N \tag{10}$$

Coefficient selection

Premasking window is often a processing of DPA before coefficient selection. There is a puzzled phenomenon that the performance of DPA is not satisfying without discarding some feature coefficients that have large DP, like DCT coefficients in low-frequency. In fact, it is not reasonable to discard low frequencies. It was explained that the variations of low frequencies are resulted from illumination variations in many existing reports. However the explanation is not reasonable because some DCT coefficients in low frequencies have large DP values. If the DCT coefficients in low frequencies are discarded arbitrarily, it is probable to lose discriminant coefficients. DCT coefficients in low frequencies may have large DP values in ORL and PolyU database shown in Figure 5(a) and (c), so they should not be discarded arbitrarily. The absolute values of direct currency and low frequencies are far larger than those of middle and high frequencies. Thus the DP of DCT coefficients in the middle frequencies, even when they have large DP values, is submerged or concealed by the DP of DCT coefficients in the low frequencies. The above is the essential reason why the performance of DPA is not satisfying without discarding some DCT coefficients in low-frequency even they have large DP values.

In our scheme, the DCT coefficients are sorted according to their DP values. n denotes the feature number after DCT coefficients selection. n DCT coefficients has the larger DP values than the other DCT coefficients that are selected.

Normalization

($x_1,x_2,\ldots,x_n$), ($y_1,y_2,\ldots,y_n$) are the feature vectors extracted from two images respectively. The components of the feature vectors are the selected DCT coefficients with large DP values. The Euclidean distance between the two feature vectors is calculated by Equation 11.

$$d = \sqrt{(x_1-y_1)^2 + (x_2-y_2)^2 + \ldots + (x_n-y_n)^2} \tag{11}$$

Suppose that x_1, y_1 are the DCT coefficients of direct currency or low-frequency. The absolute values of low-frequency coefficients are much larger than the middle-frequency coefficients, thus the discriminant ability of middle-frequency coefficients is weakened greatly without discarding low-frequency coefficients. But it is probable to lose discriminant coefficients when low-frequency coefficients are discarded arbitrarily. To settle the conflict, all selected DCT coefficients could be normalized as Equation 12.

$$A'_{ij} = \frac{A_{ij} - A\min_{ij}}{A\max_{ij} - A\min_{ij}} \tag{12}$$

The definition of A_{ij} is the same as Equation 4. $A\max_{ij}$ and $A\min_{ij}$ are the maximum and minimum in matrix A_{ij}.

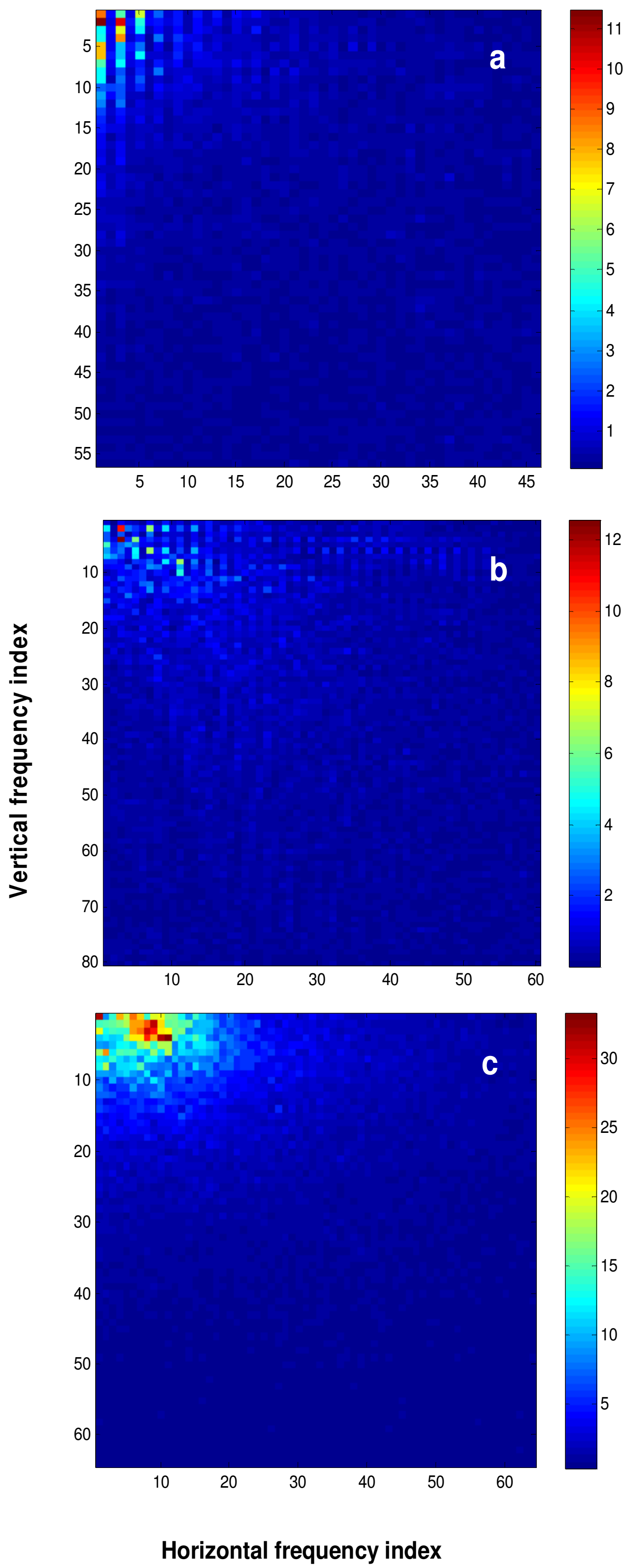

Figure 5. DP values of DCT coefficients (a) ORL (b) Yale (c) PolyU.

Dynamic weighting

The range of the normalized matrix A_{ij} is [0, 1]. The components of the normalized feature vector need to be weighted in order to improve the recognition rate. $(x'_1, x'_2, \ldots, x'_n)$, $(y'_1, y'_2, \ldots, y'_n)$ are the normalized feature vectors extracted from two images respectively. The weight of the i-th component in the vector can be determined by the ratio of its DP value to the total DP values of all selected components in the vector.

$$w_i = \frac{DPV_i}{DPV_1 + DPV_2 + \ldots + DPV_n}, i = 1, 2, \ldots, n \quad (13)$$

where DPV_i denotes the DP value of the i-th component in the vector. The components of normalized feature vectors are weighted with the given formula

$$xw_i = x'_i \cdot w_i, \; yw_i = y'_i \cdot w_i \quad (14)$$

Lastly, $(xw_1, xw_2, \ldots, xw_n)$, $(yw_1, yw_2, \ldots, yw_n)$ are the feature vectors extracted from two images by DWDPA respectively. The Euclidean distance between the two feature vectors is modified as

$$dw = \sqrt{(xw_1 - yw_1)^2 + (xw_2 - yw_2)^2 + \ldots + (xw_n - yw_n)^2} \quad (15)$$

Whole procedure

Figure 6 shows the whole procedure of DWDPA for face and palmprint recognition approach. The samples captured by face sensors and palmprint sensors constitute ORL face database, Yale face database and PolyU palmprint database respectively. The selected samples from the database constitute the train set, while the rest samples in the database constitute the test set. Although DWDPA does not need premasking, it can be combined with other existing premasking approaches to improve the discriminant ability. The experiments in the next section confirm the effect of DWDPA optimizing other approaches obviously.

EXPERIMENTS AND DISCUSSION

In order to evaluate the proposed method, the experiments are performed on ORL face database, Yale face database and PolyU palmprint database. The images are scaled down to the sizes listed in Table 1. All simulations split the datasets into train and test dataset

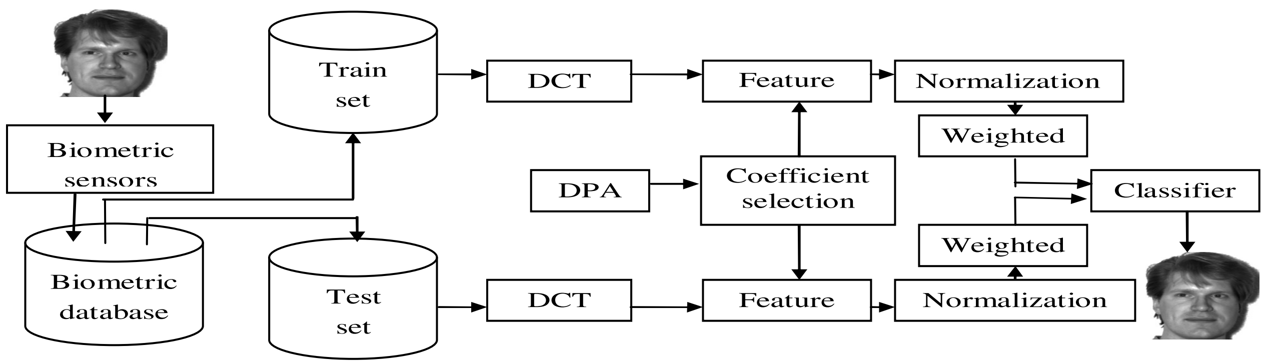

Figure 6. Whole procedure of DWDPA.

Table 1. Database and simulations details.

Database	Number of classes (C)	Number of samples in each class (S)	Train	Test	Image size	Down-sampled size
ORL	40	10	5	5	112×92	56×46
Yale	15	11	6	5	243×320	60×80
PolyU	100	6	3	3	128×128	64×64

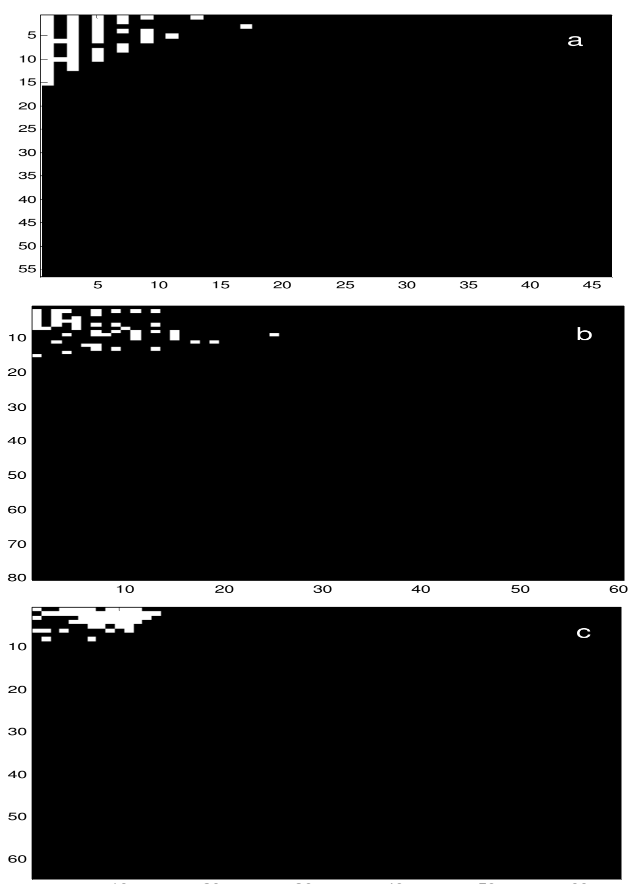

Figure 7. The location of fifty selected DCT coefficients (a) ORL (b) Yale (c) PolyU.

randomly and the results are the average of the numerous runs.

Figure 7 is the location of fifty selected DCT coefficients that have larger DP values than the other DCT coefficients on different databases.

The weight values of the DCT coefficients selected by DWDPA are shown in Figure 8 when fifty DCT coefficients are selected.

Figure 9 shows the comparison among the recognition rates of eight approaches in terms of the selected DCT coefficients numbers on ORL face, Yale face and PolyU palmprint databases. pm1 and pm2 denotes two premasking windows. [r_s r_e c_s c_e] of pm1 is [2 15 2 15], while [r_s r_e c_s c_e] of pm2 is [3 15 3 15]. Figure 10 shows the comparison among the recognition rates of seven approaches in terms of the selected DCT coefficients numbers on ORL face, Yale face and PolyU palmprint databases.

Table 2 elaborates the details of the approaches tested in Figures 9 and 10. A normal approach has three or less processes. "Nil" means nothing is used in that process. DWDPA is proposed in this paper, while the summary information of other approaches is listed in Table 3. Coefficient selection methods are categorized into two main approaches. DCT coefficients are selected according to their DP values from high to low in DPA; or DCT coefficients are selected according to their positions in the zigzag scanning order. Weighted adjustment by DWDPA depends on the processes of normalization and dynamic weighting in this paper to enhance discriminant ability. Rescaling method was proposed in Vishwakarma et al. (2007).

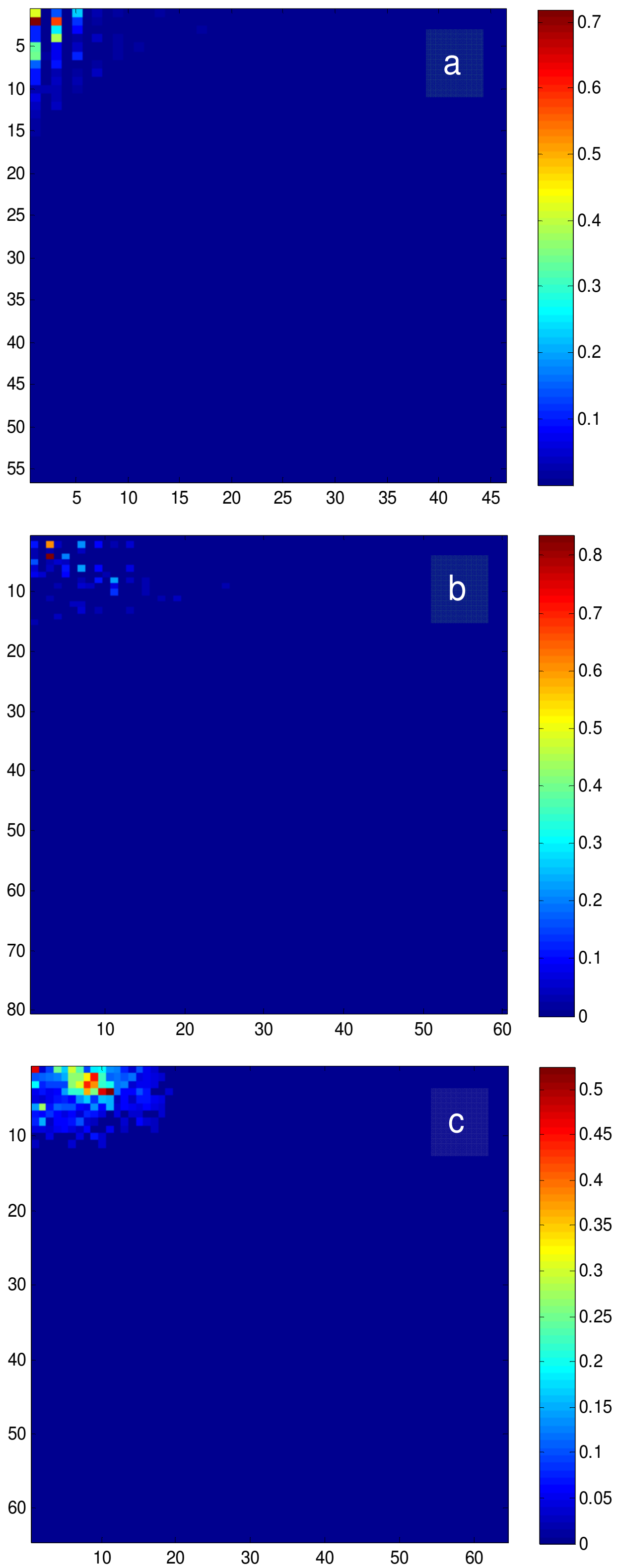

Figure 8. Weight values of the DCT coefficients selected by DWDPA (a) ORL (b) Yale (c) PolyU.

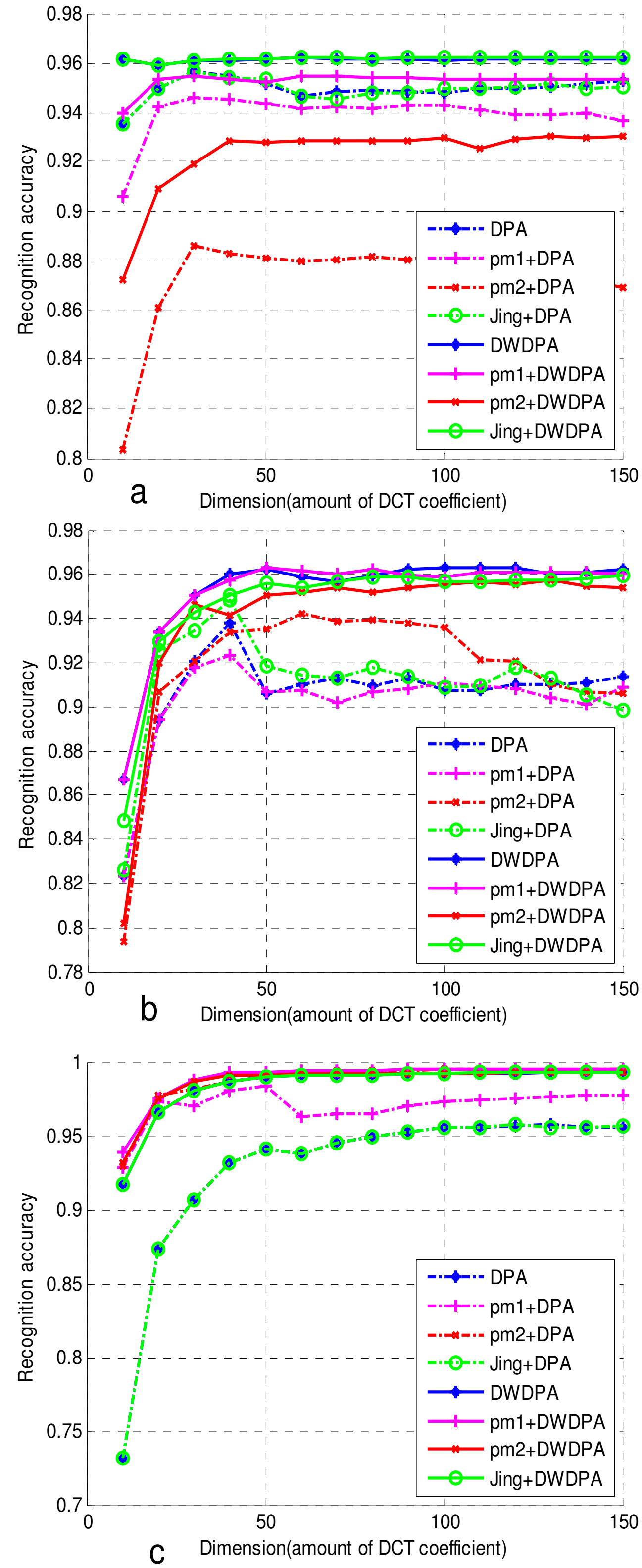

Figure 9. The comparison of recognition rates of eight approaches (a) ORL (b) Yale (c) PolyU.

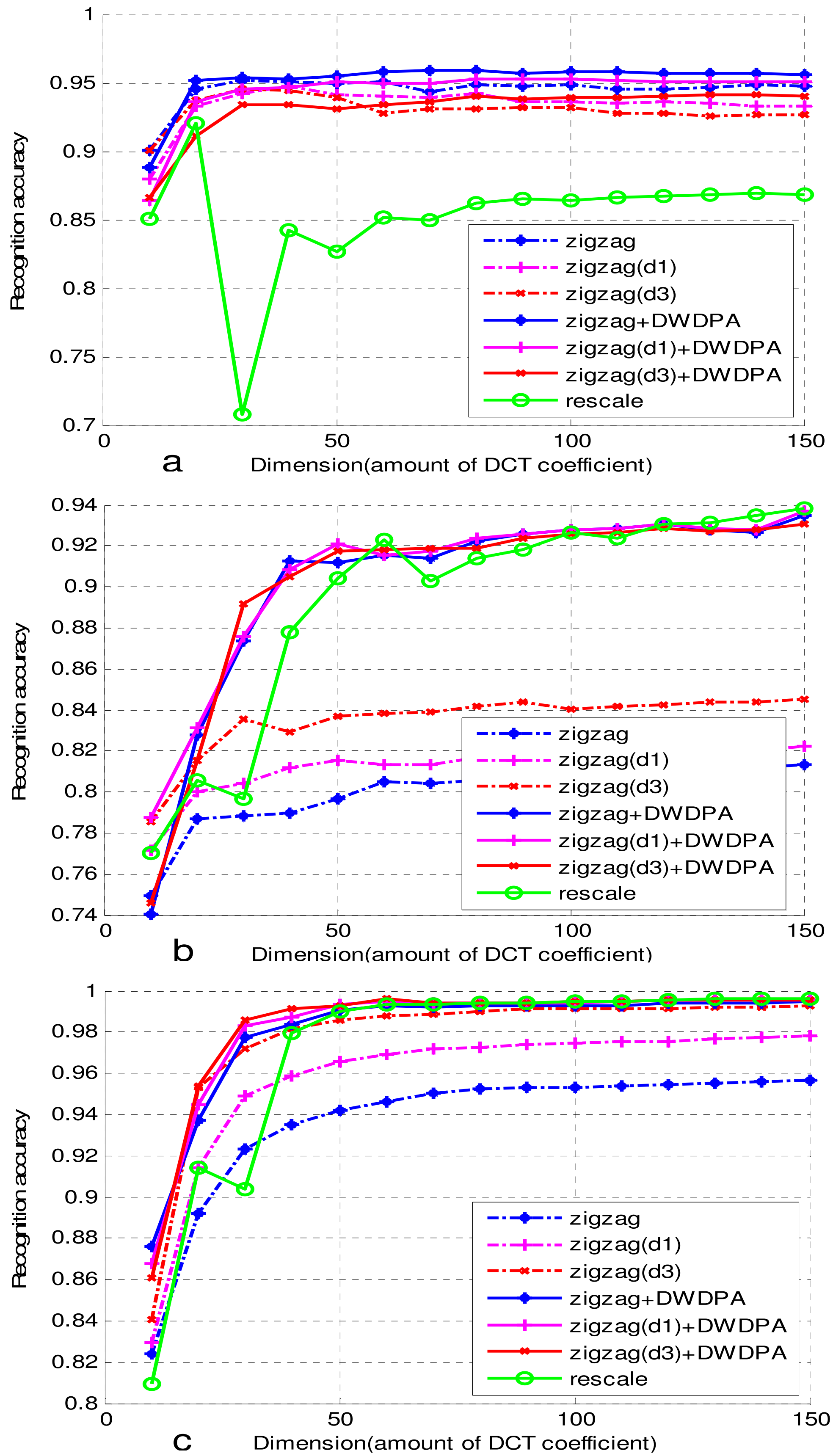

Figure 10. The comparison of recognition rates of seven approaches (a) ORL (b) Yale (c) PolyU.

Table 2. Detail elaboration of the approaches tested.

Approach	Premasking	Coefficient selection	Weighted adjustment
DPA	Nil	DPA	Nil
pm1+DPA	pm1	DPA	Nil
pm2+DPA	pm2	DPA	Nil
Jing+DPA	Jing	DPA	Nil
DWDPA	Nil	DPA	DWDPA
pm1+DWDPA	pm1	DPA	DWDPA
pm2+DWDPA	pm2	DPA	DWDPA
Jing+DWDPA	Jing	DPA	DWDPA
zigzag	Nil	zigzag	Nil
zigzag(d1)	Discard direct currency	zigzag	Nil
zigzag(d3)	Discard 3 low frequencies	zigzag	Nil
zigzag+DWDPA	Nil	zigzag	DWDPA
zigzag(d1) +DWDPA	Discard direct currency	zigzag	DWDPA
zigzag(d3) +DWDPA	Discard 3 low frequencies	zigzag	DWDPA
Rescale	Nil	zigzag	Rescaling

Table 3. Summary of the approaches in Table 2.

Approach	Authors	Year
DPA	Dabbaghchinan/Jing	2010/2004
Pm1, pm2	Dabbaghchian	2010
Jing's approach	Jing and Zhang	2004
Zigzag (d1), zigzag (d3)	Er and Chen	2005
Rescaling	Vishwakarma	2007

From the experiments, some results are discussed and summarized as follows:

(1) The recognition rates of DWDPA in Figures 9 and 10 are higher than those of DPA. Moreover, although DWDPA does not need premasking, it can be combined with other existing premasking approaches to improve the discriminant ability. The experiments confirm the effect of DWDPA optimizing other approaches obviously. The recognition accuracies of the existing methods without DWDPA are lower than those methods combined with DWDPA. In Figure 9, DWDPA, pm1+DWDPA, pm2+DWDPA, Jing+DWDPA have all higher recognition rates than DPA, pm1+DPA, pm2+DPA, Jing+DPA respectively. In Figure 10, zigzag+DWDPA, zigzag(d1)+DWDPA, zigzag(d3)+DWDPA have all higher recognition rates than zigzag, zigzag(d1), zigzag(d3). It is obvious that DWDPA has a nice and wide optimizing effect to enhance discriminant ability, thus it can be easily employed as the post-processing in the existing approaches.

(2) The performance of the premasking depending on the specific circumstances of different databases is not stable.

In Figure 9(a), the recognition rate of pm1+DPA is higher than that of pm2+DPA on ORL database. The recognition rate of pm1+DWDPA is higher than that of pm2+DWDPA on ORL database. The reason can be explained as follows. There is less illumination variance in ORL face database, so the DCT coefficients in low frequencies are caused mainly by the people's complexion. Of course, people's complexion is also a useful facial feature, thus DCT coefficients in low frequencies in ORL face database have useful discriminant information. pm2 discards more DCT coefficients in low frequencies, thus the recognition rates of pm2 is lower.

In Figure 9(b), the recognition rate of pm1+DPA is lower than that of pm2+DPA on Yale database. The recognition rate of pm1+DWDPA is higher than that of pm2+DWDPA on Yale database. There is great illumination variance in Yale face database, so the DCT coefficients in low frequencies are caused mainly by illumination change that disturbs recognition. pm2 discards more DCT coefficients in low frequencies caused by illumination variance, thus the recognition rates of pm2 is higher. However, the low frequencies are not caused only by illumination, but also people's complexion and other facial feature. DWDPA does not discard DCT coefficients in low frequencies directly, but dynamically give the different weights to DCT coefficients, so the recognition rates of the methods combined with DWDPA are enhanced.

In Figure 9(c), the recognition rate of pm1+DPA is lower than that of pm2+DPA on PolyU database. The palmprint images are captured in two sessions. There was few months interval between the two sessions, so there was also illumination variance among the palmprint images. It is hard to compare the performance of pm1+DWDPA and pm2+DWDPA on PolyU database.

In a word, it is difficult to ensure which premasking window is optimized when the existing methods are not combined with DWDPA.

(3) A similar phenomenon can be seen in Figure 10. On ORL database in Figure 10(a), the recognition rate of zigzag(d1) is higher than that of zigzag(d3). DCT coefficients in low frequencies in ORL face database have also useful discriminant information because less illumination variance exists in ORL face database. The approaches discarding more DCT coefficients in low frequencies have lower recognition rates than those discarding less DCT coefficients in low frequencies, vice versa. Thus the results on Yale and PolyU databases are contrary to those on ORL database shown in Figure 10 (b) and (c). Illumination variance in Yale and PolyU databases is larger than that in ORL database. It is reasonable to discard more DCT coefficients in low frequencies if the illumination variance is large. However, DWDPA does not need to consider this problem to improve its performance thanks to its adaptive weighting. zigzag+DWDPA, zigzag(d1)+DWDPA and zigzag(d3)+DWDPA have similar recognition rates in three databases.

(4) DWDPA is more robust on various databases. The recognition rates of DWDPA (or DWDPA combined approaches) are the best or approximate to those best recognition rates in each diagram. Furthermore, DWDPA is insensitive to the shape and size of premasking windows when the illumination variance is large. The approaches combined with DWDPA on Yale and PolyU databases (Figure 9b and c); Figure 10 b and c)) have the approximate recognition rates. The recognition rates of approaches combined with DWDPA on ORL databases (Figure 9a; Figure 10a differ a little due to the losing of DP of DCT coefficients in low frequency.

(5) The rescaling approach is not stable. The rescaling constant cannot be adjusted according to different databases, so it does not have a wide adaptability to various circumstances. The curves of rescaling approach are more fluctuant.

(6) In Figure 9a and c, the curve of Jing+DPA is approximate to that of DPA; and the curve of Jing+DWDPA is approximate to that of DWDPA. It indicates that the results of coefficient selection after Jing's premasking is similar to the results of coefficient selection of DWDPA and DPA without premasking on ORL and PolyU databases.

Conclusions

This paper explains the phenomenon why the recognition rate is low without discarding the low-frequencies DCT coefficients more reasonably than the existing reports. Besides, the dynamic weighted approach preserves more DCT coefficients with high DP reasonably and avoids losing discriminant coefficients. Improper masking weakens and even deteriorates the performance of the system in the existing methods. DWDPA without premasking window does not need to optimize the shape and size of premasking window. Of course, it does not have the problem caused by improper masking. Due to normalization, the DCT coefficients with large absolute value avoid destroying the DP of the other DCT coefficients that have less absolute value but high DP values. Dynamic weighting gives larger weights to the DCT coefficients with larger DP values.

Sufficient experiments prove that DWDPA outperforms DPA in DCT domain for face and palmprint recognition obviously. It can be employed in the existing approaches as post-processing to effectively enhance discriminant ability. Also DWDPA can achieve well performance and be directly generalized in other databases because the weights of feature components are weighted adaptively.

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