Fingerprint enhancement using multi-scale classification dictionaries with reduced dimensionality

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***Abstract*: In order to improve the quality of fingerprint with large noise, this paper proposes a fingerprint enhancement method by using a sparse representation of learned multi-scale classification dictionaries with reduced dimensionality. Multi-scale dictionary is used to balance the contradiction between the accuracy and the anti-noise ability, which has been shown to be an ideal solution to reconcile the demands of enhancement quality and computational performance. Principal component analysis (PCA) is applied in our technique for dimension reduction of multi-scale classification dictionaries. Under the quality grading scheme and multi-scale composite windows, the fingerprint patches are enhanced by using a sparse representation of learned multi-scale classification dictionaries with reduced dimensionality according to their priorities. In addition, the multi-scale composite windows help the more high quality spectra diffuse into the low quality fingerprint patches and this can greatly improve the spectra quality of them. Experimental results and comparisons on FVC 2000 and FVC 2004 databases are reported. And it shows that the proposed method yields better result in terms of the robustness of fingerprint enhancement as compared with latest techniques. Moreover, the results show that the proposed algorithm can obtain better identification performance.**

1. Introduction

Fingerprints are the most common biometrics used for personal identification in commercial and forensic areas [1-4]. The fingerprint image enhancement is a crucial task for most automatic fingerprint identification systems (AFIS). A fundamental requirement in AFIS is to extract reliable and faithful fingerprint features from fingerprint images even with poor quality [5]. We have to enhance fingerprint to improve performance of minutiae extraction algorithms.

In recent years, various solutions have been proposed to enhance the fingerprint images [6-17]. Hong et al. [6] employed even symmetric Gabor filter in fingerprint filtering process, which is considered to be one of the most popular fingerprint enhancement methods. The filter is designed according to two parameters: ridge orientation and ridge frequency, and is used as band-pass filter to reduce the undesired noise and preserve the true ridge and valley structures of fingerprint images. However, Gabor filters have two main limitations [7]: the maximum bandwidth of a Gabor filter is limited to approximately one octave; and Gabor filters are not optimal if one is seeking broad spectral information with maximal spatial localization. Furthermore, the signal orthogonal to the local orientation in fingerprint images does not always result in an ideal sine wave [8]. In order to overcome the drawbacks, some modified methods based on Gabor filter have been proposed to meet the need of low quality fingerprint image enhancement [10-14]. These methods show a potential in fingerprint image enhancement in comparison to classical Gabor filter methods.

Chikkerur et al. [15] proposed a filtering method to enhance fingerprint image by using short time Fourier transform (STFT). In this method, they designed a directional band-pass filter to improve the quality of the fingerprint image. Similar to [6], this method also need to use the parameters of patch frequency and orientation. The parameters involved in the filters are very difficult to be accurately computed by using a simple STFT. Sutthiwichaiporn et al. [16] employed an adaptive boosted spectral filtering (ABSF) to enhance fingerprint image. In their method, the fingerprint image is divided into patches in spatial domain and the patches are enhanced using a Gaussian-matched filter according to their quality grades. This strategy can iteratively propagate higher-quality spectra of enhanced patches to lower-quality patches to be enhanced. This helps improve the quality of the patches with large noise. The fingerprint ridge signal noise suppression and the fingerprint patch quality evaluation are the key to success. In [16], the authors used the percentile of high spectra as an empirical threshold to evaluate the ridge signal. However, the ridge signal spectra are unevenly distributed in different patches. Consequently, this approach is not appropriate to estimate the ridge signal and may lead to bad results of enhancement. As a fingerprint ridge is in general of an obvious orientation characteristic, using a 2D angular-pass filter (APF) with orientation-selectivity obviously helps to remove the noise spectra in a patch signal. In view of this, Ding et al. [17] designed a robust 2D adaptive Chebyshev band-pass filter (ACBF) with orientation-selectivity to enhance fingerprint based on the quality grading scheme. It succeeded with the aid of spectra diffusion. Comparing with the method in [16], its effects are better in terms of noise suppression and ridge signal preservation. Under the quality grading scheme, the fingerprint patches are enhanced based on its own quality grade. It means that the higher quality patches will be enhanced before the lower quality patches. So, it can ensure that the higher quality spectra diffuse into lower quality patches with the help of the scheme of patch quality grading. Bian et al. [18] designed a collaborative filtering model for enhancing fingerprint image, where the Gabor filter and linear contrast stretching (LCS) are employed to pre-enhance the original fingerprint, and subsequently enhancing the pre-enhanced fingerprint using the collaborative model.

Recently, the sparse representation theory in image processing arouses widespread concern [19]. It has made great achievements in face recognition [20, 21], image denoising [22, 23], image super-resolution [24, 25] and image fusion [26, 27]. The relatively less active research on fingerprint image sparse representation also starts to attract the researcher's attention. [28-31]. The focuses of these researches are mainly on exploring new and efficient methods to improve the performance of the AFIS, and some achievements and progresses have been made recently in this area.

In order to overcome the limitations of the Gabor filter, Ding et al. [31] used a sparse representation-based classification dictionaries learning (CDL) to enhance the fingerprint image. According to the ridge orientation patterns, the authors classify the fingerprint patches into different classes and separately learn classification sparse representations to capture the more accurate ridge prior information. The proposed method improves the performance of fingerprint enhancement to some extent. However, there are some limitations and flaws in their method. The sparse representation-based dictionary learning for fingerprint enhancement is highly computationally expensive. Furthermore, the fingerprint is enhanced based on the dictionary with a single scale which cannot provide a good balance between the accuracy and the anti-noise ability of the enhanced fingerprint.

To overcome the above mentioned limitations and flaws in [31], in this research, we propose a robust fingerprint enhancement via sparse representation over learned multi-scale classification dictionaries with reduced dimensionality. In fact the anti-noise ability of fingerprint patch enhancement varies in relation to the patch size. It is weakened when the patch is small and is strengthened when the patch is large. On the other hand, the smaller the size of a patch, the higher the accuracy of the enhancement. In other words, the distortion of the enhanced fingerprint patch becomes more noticeable when the patch size is enlarged. In this paper, the fingerprint image is enhanced by using the quality grading scheme, where the higher quality patches are enhanced using the dictionary with smaller size. By doing so, it is not only to be able to obtain a good balance between the accuracy and the anti-noise ability of enhanced fingerprint, but also can significantly reduce the computational complexity of proposed method.

As described in [31], comparing to a generic image, a fingerprint image has an intrinsic ridge pattern. Reliable estimation of fingerprint ridge orientations is a fundamental prerequisite for a good image enhancement [32]. Data dimensionality reduction algorithm is a very important tool and methods to transform data from a high dimensional space to a low dimensional space to reveal the intrinsic structure of complex data [33, 34]. Instead of learning a shared sparse representation for all fingerprint patches, the proposed method learn classification dictionaries for each class training dataset by using dimension-reduced dictionaries achieved by the Principal Component Analysis (PCA). It can better capture the intrinsic ridge pattern prior. The fingerprint is enhanced by using multi-scale dictionaries and spectra diffusion based on the patches quality grading scheme. This is achieved by using the multi-scale window and quality assessment approach. Ideally, in a local neighborhood, fingerprint ridges and valleys form a sine wave which has a distinct orientation and frequency. Therefore, in order to improve the performance of algorithm, we learn the classification dictionaries with reduced dimensionality and different scales in frequency domain.

The rest of the paper is organized as follows. The discussion on fingerprint pre-enhancing is provided in Section 2. The fingerprint patch dimension reduction techniques based on Principal Component Analysis (PCA) is introduced briefly in Section 3. In Section 4 we describe how to construct the multi-scale classification dictionaries with reduced dimensionality and the proposed fingerprint enhancement method is described in detail in Section 5. Experiments conducted and relevant analysis are given in Section 6. Finally, some conclusions of this research are drawn in Section 7.

2. The fingerprint image pre-enhancement

To improve the fingerprint image quality, we first enhance original fingerprint image using Gabor filtering and thus improve the regions with weak noise. The details of this procedure are described in literature [6]. The even-symmetric Gabor filter has the general form below,

$$G(x,y;\theta,f)=\exp\left\{-\frac{1}{2}\left[\frac{x_\theta^2}{\delta_x^2}+\frac{y_\theta^2}{\delta_y^2}\right]\right\}\cos(2\pi f x_\theta) \tag{1}$$

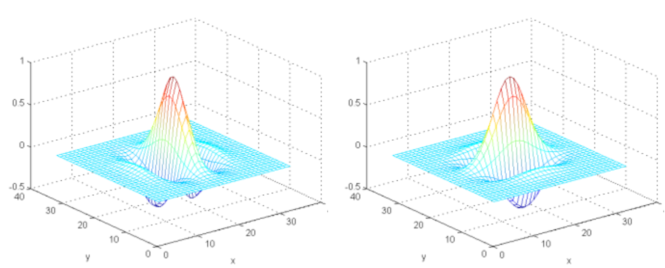
$$x_\theta = x\cos\theta + y\sin\theta \tag{2}$$

$$y_\theta = -x\sin\theta + y\cos\theta \tag{3}$$

where θ is the orientation of the Gabor filter, f is the frequency of a sinusoidal plane wave, and δ_x and δ_y are the space constants of the Gaussian envelope along x and y axes, respectively. The spatial characteristics of Gabor filter are illustrated in Fig. 1.

Hong et al assumed that fingerprint ridge have distinct orientation and frequency in local region and form an ideal sine wave [6]. Therefore, if we can input the accurate ridge orientation and frequency into Gabor filters, then the noises in fingerprint ridge signal can be removed while preserving the genuine ridge and valley structures.

However, in fact this assumption in [6] is unreliable because some ridges will not form sine waves in some regions (especially in the regions with low quality). Nevertheless, a better algorithm should be able to enhance the low quality



(a) (b)

Fig.1. *Examples of even-symmetric Gabor filter in the spatial domain. (a) The Gabor filter with f=0.1,* $\delta_x=\delta_y$ *=4.0,* $\theta=0^\circ$*. (b) The Gabor filter with f=0.1,* $\delta_x=\delta_y$ *=4.0,* $\theta=90^\circ$*.*

regions. Fig. 2 (b) gives an example to illustrate the enhancement results using Gabor filter. The sample fingerprint image is taken from FVC2000 DB1_B 108_6. As we can see from this example, Gabor filter does improve noticeably the quality of input fingerprint images in the regions with weak noise, but it does little to enhance the regions with strong noise.

In fact, in the fingerprint image enhanced by Gabor filter, the gray level of a pixel in a fingerprint image constitutes approximately 50 percent of the total grayscale space or lower. This undoubtedly shrinks fingerprint image contrast space and weakens its contrast. In this research, we use the LCS [18] to enhance the contrast of fingerprint enhanced by Gabor filter [18]. As is shown in Fig. 2 (c), using LCS to enhance fingerprint contrast can significantly improve the fingerprint quality, also it can well preserve the ridge information.

(a) (b) (c)

Fig.2. *Fingerprint image pre-enhancement. (a) the original fingerprint image, (b) the fingerprint image enhanced by Gabor filter, (c) the fingerprint image contrast enhancement by the LCS . The original fingerprint image comes from FVC2000 DB1_B 108_6.*

3. Dimensionality reduction based on PCA

In the training and enhancing algorithms, the computational complexity and the dimensionality of samples are closely related. Performing dimensionality reduction to the samples will correspondingly reduce the computational cost in the subsequent dictionary learning and fingerprint enhancing.

One of the problems in high-dimensional datasets is that, in many cases, not all the measured variables are "important" for understanding the underlying phenomena of interest. Those less important factors can be removed by performing the PCA, a commonly used mathematical algorithm that can dramatically reduce the dimensionality of the data without losing much information for the key factors in the data set. PCA is, in the sense of mean-square error, the best linear dimension reduction technique [35]. In essence, PCA seeks to reduce the dimension of the data by finding a few orthogonal linear combinations (the PCs) of the original variables with the largest variances [36]. The first principal component is the linear combination of variables corresponding to the largest variance, and the second principal component corresponds to the linear combination of variables associated with the second largest variance, and so on. In general, for data sets with many variables, only several of the bigger variances of the principal components are important, all those smaller variances associated with the rest of principal components can be ignored without losing much information. This is usually referred to as dimensionality reduction of a data set.

The fingerprint sample patches, partitioned as $W \times W = n$ pixel patches in spatial domain, are represented as $\mathbf{F}_m \in \square$ of n dimensions, and their corresponding spectra in frequency domain are represented as $\mathbf{F}_{sm} \in \square$. To reduce the dimension of fingerprint patches spectra, we apply the PCA on these patch vectors $\mathbf{F}_{sm}, m = 1, 2, \cdots$, and seek a subspace on which these vectors could be projected while preserving 99.9% of their average energy. The projection matrix that transforms the patch spectra $\mathbf{F}_{sm} \in \square$ to corresponding reduced feature spectra $\tilde{\mathrm{I}}_{sm} - \square$, $n>>k$, is defined as $\mathbf{P} \in \square$. And then, the reduced patch spectra $\tilde{\mathrm{I}}_{sm} - \square$ can be obtained:

$$\tilde{\mathrm{I}}_{sm} \quad - - _{sm} \tag{4}$$

4. The construction of multi-scale classification dictionaries with reduced dimensionality

In order to achieve reasonable classification dictionaries to enhance the fingerprint, in this paper the ridge pattern prior and the patch size of the fingerprint are used to boost dictionary learning and fingerprint enhancement. In the following, we first address how to assess the quality of fingerprint patches, and then present the model of the multi-scale classification dictionaries with reduced dimensionality.

4.1. The quality assessment of fingerprint patches

There are two aspects to the assessment of the quality of a fingerprint patch: one is to build a reliable training patch set, and the other is to ensure that the higher quality fingerprint patches can be enhanced before the lower quality fingerprint patches. We assess the fingerprint patch quality using the coherence of point orientation in the patch [37, 38]. It can ensure that the high quality patches are assessed reliably. It may mistakenly classify some higher quality patches (e.g., singularity area) for lower quality ones only in rare cases, but it rarely misclassifies the lower quality patches as higher quality ones. That is what we need.

According to the level of coherence of a patch, the fingerprint patch quality can be grouped into high, medium, low or poor. The coherence *Coh,* which ranges from 0 to 1, is estimated based on weighted linear projection analysis proposed by Bian et al. [38]. The type of patch quality $Q_{p(x,y)}$ can be defined as follow:

$$Q_{p(x,y)} = \begin{cases} 1 & if \quad Coh \in [0.9, \ 1] \\ 2 & if \quad Coh \in [0.8, \ 0.9) \\ 3 & if \quad Coh \in [0.7, \ 0.8) \\ 4 & otherwise \end{cases} \tag{5}$$

The values 1, 2, 3 and 4 correspond to the quality types of High, Medium, Low and Poor respectively. Fig. 3 gives an example of patch quality assessment and classification. As can be observed from the figure, the classification result is consistent with our expectations.

4.2. Multi-scale classification reduction dictionaries

Fingerprint ridge has a cyclical character in local region, which is well suited to frequency domain analysis. To get better performance, in a typical fingerprint enhancement algorithm fingerprint is partitioned in spatial domain first, and then is enhanced in frequency-domain. In this research, we propose to learn multi-scale classification reduction dictionaries from the corresponding spectrum training patch sets. To balance the

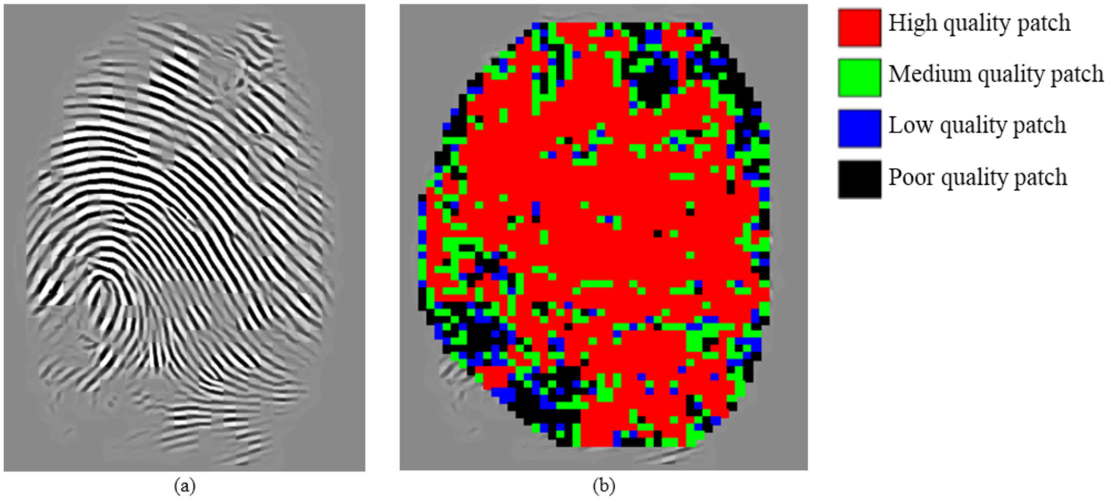


Fig.3. *An example of the quality of patch assessment: (a) the pre-enhanced fingerprint, (b) the assessment result.*

contradiction between the accuracy and the anti-noise, we learn the multi-scale dictionaries for enhancing fingerprint patches with different qualities. Furthermore, in order to obtain more reliable prior knowledge we learn C number of classification dictionaries in each scale. First of all, we build the training patch sets with different sizes separately. Then, the training patches with the same size are divided into C groups based on their own ridge orientation patterns. In the end, to further obtain more accurate ridge prior information, the quality of patches are assessed using the method described in Section 4.1, and the high quality patches in each of the training set are selected to build the ultimate training patch set. Before learning dictionary, all training patches are transformed to frequency domain using the 2-D discrete Fourier transform, and the patch spectra training sets are built. The 2-D discrete Fourier transform can be defined as follow:

$$\mathbf{F}_{p(x,y)}(u,v)=\frac{1}{W^2}\sum_{m=0}^{W-1}\sum_{n=0}^{W-1}\mathbf{Y}_{p(x,y)}(m,n)e^{\frac{-2\pi j(mu+nv)}{W}} \tag{6}$$

where $\mathbf{F}_{p(x,y)}(u,v)$ are the corresponding Fourier coefficients of $\mathbf{Y}_{p(x,y)}(m,n)$.

For notational convenience, let $\mathbf{Y}_s=\{\mathbf{Y}_{s1},\mathbf{Y}_{s2},\cdots$ be the sampled training fingerprint patches using a pre-specified scale s and $\mathbf{F}_s=\{\mathbf{F}_{s1},\mathbf{F}_{s2},\cdots$ the corresponding set of patch spectra, where $\mathbf{Y}_{si}\in$, $\mathbf{F}_{si}\in$ $\cdots$. The patch spectra are the magnitude of the Fourier transform. Let $\boldsymbol{\theta}=\{\theta_1,\theta_2,\cdots$ be the patch orientations computed using the approach described in [38] based on sample set $\mathbf{Y}_s$, then all fingerprint patches are divided into C groups according to different patch orientations $\boldsymbol{\theta}$ as

$$\mathbf{Y}_s=\{\mathbf{Y}_s^1,\mathbf{Y}_s^2,\cdots,\mathbf{Y}_s^C,\} \tag{7}$$

where

$$\mathbf{Y}_s^i=\{\mathbf{Y}_{s1}^i,\mathbf{Y}_{s2}^i,\cdots,\mathbf{Y}_{sM}^i,\}, i=1,2,\cdots,C$$

and then the patch spectra set $\mathbf{F}$ are obtained

$$\mathbf{F}_s=\{\mathbf{F}_s^1,\mathbf{F}_s^2,\cdots,\mathbf{F}_s^C,\} \tag{8}$$

where

$$\mathbf{F}_s^i=\{\mathbf{F}_{s1}^i,\mathbf{F}_{s2}^i,\cdots,\mathbf{F}_{sM}^i,\}, i=1,2,\cdots,C$$

where M is the training sample size of a class.

For each classification, we firstly apply the PCA algorithm on the training set $\mathbf{F}_s^i$, and get the projection matrix $\mathbf{P}^i\in$, and then the dimensionality reduced training set $\tilde{\Gamma}_s$ can be obtained:

$$\tilde{\Gamma}_s \quad {}_s \tag{9}$$

The dictionary is learned from the corresponding training set $\tilde{\Gamma}_s$. The K-SVD dictionary learning algorithm [39] is applied to the training set, resulting the dictionary $\mathbf{D}_s^i\in$:

$$\mathbf{D}_s^i=\arg\min_{\mathbf{D}_s^i,\boldsymbol{\Gamma}_s^i}\left\|\tilde{\mathbf{F}}_s^i-\mathbf{D}_s^i\boldsymbol{\Gamma}_s^i\right\|_F^2 \tag{10}$$

$$s.t\ \forall k\ \|\boldsymbol{\gamma}_k\|_0\le L, i=1,2,\cdots,C; k=1,2,,\cdots,K$$

Where L is the sparsity constrained item, K is the size of each class dictionary, γ_k is the sparsity representation coefficient vectors that corresponding to the training patches with reduced dimensionality. The dictionary $\mathbf{D}_s^i$ associated with a given scale s can be described as

$$\mathbf{D}_s=\{\mathbf{D}_s^1,\mathbf{D}_s^2,\cdots \tag{11}$$

Let $\mathbf{D}_0$ be the initial dictionary. In general, $\mathbf{D}_0$ contains a lot of redundant information so that it can provide a sufficient representation for almost all possible fingerprint patterns and can characterize all sorts of spectra structures and details of fingerprints. In practice, $\mathbf{D}_0$ is initialized as the discrete cosine transform (DCT) overcomplete dictionary. DCT can in general provide an appropriate representation of fingerprint spectra. To create a more optimal dictionary, the K-SVD algorithm is used to remove the redundant information in the initial dictionary $\mathbf{D}_0$. The K-SVD algorithm typically includes two phases: sparse coding and dictionary updating. In the phase of sparse coding, the input signals in $\tilde{\Gamma}_s$ are sparse-coded for the given estimation to the current dictionary, which produces a sparse representation matrix $\boldsymbol{\Gamma}_s^i$. In the phase of dictionary updating, the dictionary atoms are updated for the currently given sparse representations. In order to improve efficiency of dictionary learning, in proposed algorithm, the orthogonal matching pursuit (OMP) [40] is employed in the phase of sparse coding.

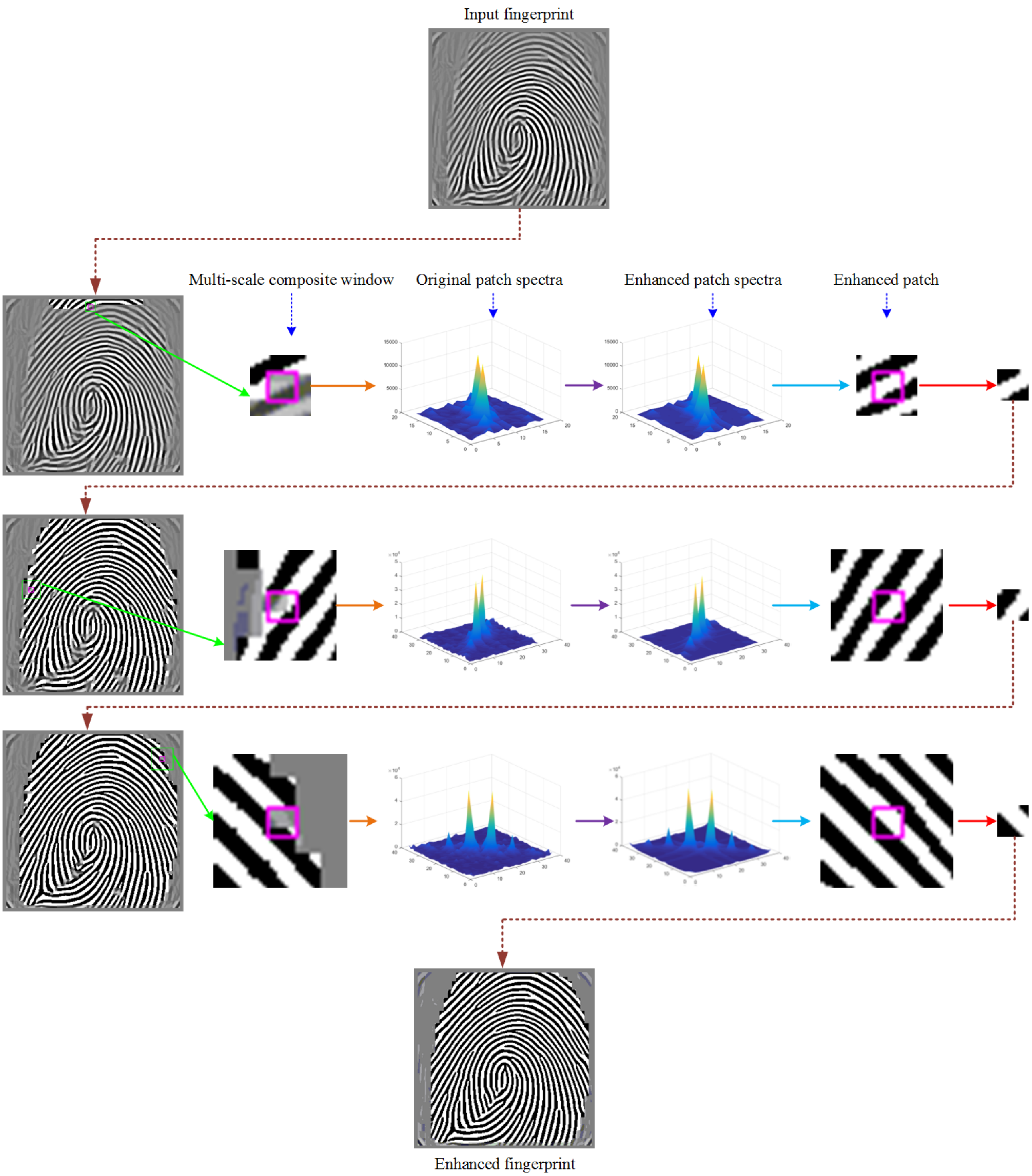


Fig.4. *Illustration of a sequence of operations performed by our proposed method.*

5. Fingerprint enhancement based on multi-scale classification dictionaries with reduced dimensionality

In our algorithm, the fingerprint is enhanced by using the quality grading scheme and the strategy of the multi-scale composite windows (MCW). It makes the patches with higher quality being enhanced by just using the dictionaries with smaller sizes. Our proposed fingerprint enhancing process method is illustrated in Fig. 4.

5.1. The fingerprint patch enhancement

Once the multi-scale classification reduction dictionaries $\{\mathbf{D}_s^i\}$ are constructed, the fingerprint patch enhancement phase attempts to reconstruct an enhanced patch $\hat{\mathbf{y}}_s$ from an original input patch $\mathbf{y}_s$ ($\mathbf{y}_s \in \square^{\cdot\cdot}$), and they have the same size *s*. The patch enhancement can be performed in the following steps:

Step 1). Estimate the patch orientation $\mathbf{y}_s$ by using the method proposed in [38]. The patch is then divided into corresponding class *i* based on the computed orientation.

Step 2). Transform patch $\mathbf{y}_s$ into frequency domain according to Eq. (6), which generates patch spectra $\mathbf{f}_s$. The DC spectrum in $\mathbf{f}_s$ is then removed by replacing them with zero. The patch spectra $\hat{\mathbf{f}}_s \in \square$ with reduced dimension can be obtained by transforming the patch spectra $\mathbf{f}_s$ using the projection matrix $\mathbf{P} \in \square$:

$$\hat{\mathbf{f}}_s = \mathbf{P}\mathbf{f}_s \tag{12}$$

Step 3). Apply the OMP algorithm to the patch spectra $\hat{\mathbf{f}}_s$, and calculate the sparse representation vector $\boldsymbol{\gamma}^* \in \square$ using the corresponding dictionary $\mathbf{D}_s^i$ according to the patch size and the patch classification obtained in step 1).

$$\boldsymbol{\gamma}^* = \min_{\boldsymbol{\gamma}} \left\{ \left\| \hat{\mathbf{f}}_s - \mathbf{D}_s^i \boldsymbol{\gamma} \right\|_2^2 + \lambda \left\| \boldsymbol{\gamma} \right\|_1 \right\}, \quad i = 1, 2, \cdots \tag{13}$$

Step 4). Transform the sparse representation vector γ^* using the dictionary $\mathbf{D}_s^i$ to generate the enhanced patch spectra $\bar{\mathbf{f}}_s \in \square$:

$$\bar{\mathbf{f}}_s = \mathbf{D}_s^i \boldsymbol{\gamma}^* \tag{14}$$

Step 5). Restore the enhanced patch spectra $\bar{\mathbf{f}}_s$ to the size of original patch. This can be achieved by transforming $\bar{\mathbf{f}}_s$ using $\mathbf{P}^{\mathrm{T}}$. Thus, the enhanced patch spectra $\mathbf{f}_s^E \in \square$ can be computed by

$$\mathbf{f}_s^E = \mathbf{P}^T \bar{\mathbf{f}}_s \tag{15}$$

Step 6). Calculate the enhanced patch Fourier coefficients by multiplying the enhanced patch spectra $\mathbf{f}_s^E$ with the Fourier coefficients $\mathbf{F}_{p(x,y)}(u,v)$ of original patch:

$$\hat{\mathbf{F}}_{p(x,y)}(u,v) = \mathbf{F}_{p(x,y)}(u,v)\mathbf{f}_s^E \tag{16}$$

Step **7).** Generate the enhanced patch $\hat{\mathbf{y}}_{p(x,y)}$ in the spatial domain by performing 2D inverse fast Fourier transform:

$$\hat{\mathbf{y}}_{p(x,y)}(m,n) = \sum_{u=0}^{W-1} \sum_{v=0}^{W-1} \hat{\mathbf{F}}_{p(x,y)}(u,v) e^{\frac{2\pi j(mu+nv)}{W}} \tag{17}$$

Step 8). The intensity of the enhanced ridge always in $\hat{\mathbf{y}}_{p(x,y)}$ is far less than zero. On the contrary, it always is far greater than zero in the valley or background. So the final binary representation of the enhanced fingerprint patch can be achieved by transforming $\hat{\mathbf{y}}_{p(x,y)}$ into binary image in the following way:

$$\hat{\mathbf{y}}_{p(x,y)}(m,n) = \begin{cases} 255, & if\ \hat{\mathbf{y}}_{p(x,y)}(m,n) > 0 \\ 0, & otherwise \end{cases} \tag{18}$$

5.2. The fingerprint image enhancement

With our proposed algorithm, the pre-enhanced fingerprint image is first partitioned into patches with a pre-specified size W_{in} in spatial domain. These patches are then transformed into frequency domain and enhanced iteratively in a certain order.
As discussed in Section 1, the enhanced fingerprint is more accurate but more sensitive to noise if we use a small scale window; on the other hand, while using a large scale window can have better tolerance to noise interference, it will lead to an accuracy drop. To balance the contradiction between the accuracy and the noise tolerance, we use the MCW to enhance the patches with different qualities. The MCW consists of an inner window and several outer windows with different sizes, they all possess the same central point, as shown in Fig. 5. In essence, it is similar to that described literatures [37, 38]. The difference is that our composite window method is multi-scale-based, not a single scale-based. As can be seen later, the use of multi-scale windows is of vital importance in the enhancement of patches with different qualities.

The use of MCW has two benefits. One is that the patches with different quality can be enhanced by using the classification dictionaries with a proper scale. Not only can it better improve the quality of patch, but it can also reduce the complexity of computation. The other is that it can ensure the achievement of spectra diffusion and further improve the quality of patch.

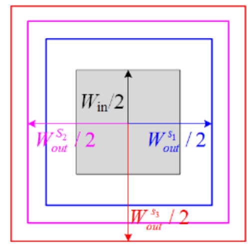


Fig.5. *The multi-scale composite windows.*

We begin enhance patches by evaluating the candidate patches according to two criteria in order to prioritize them for further processing. The two criteria are the quality and neighborhood priority of patch. The quality of patches are assessed by the method described in Section 4.1. The neighborhood priority P_{Nei} of patch is given as:

$$P_{Nei} = \begin{cases} 1, & if\ Num_{Nei} \geq 6 \\ 2, & if\ 5 \geq Num_{Nei} \geq 4 \\ 3, & otherwise \end{cases} \tag{19}$$

where Num_{Nei} is the number of enhanced patches in 8-neighborhoods. The possible values of P_{Nei} are: 1, 2 or 3, corresponding to the neighborhood priority types High, Medium and Low respectively.
The next step is prioritizing and enhancing. The priority of patches are determined only by the quality of patches in the initial state. In this stage, all high quality patches are enhanced by using the classification dictionaries with smaller sizes, and the all enhanced patches are fed into the fingerprint enhancement process simultaneously. During the following iteration process, the priority of a patch is determined according to the quality and the neighborhood priority of it, as follows. First, the non-enhanced patches with the highest quality are selected as candidate patches. And then, the neighborhood priority of these candidate patches are calculated using Eq. (19). Finally the patches with the highest neighborhood priority are enhanced in current iteration process. When all non-enhanced patches are enhanced, the iteration stops.

In our proposed algorithm, we perform fingerprint enhancement in the frequency domain, and multi-scale composite windows are used to enhance the patches with different quality. In the composite window, the patch to be enhanced is the inner patch. In order to further assist spectrum diffusion, we use a smaller scale slide window to introduce more high quality spectrum.

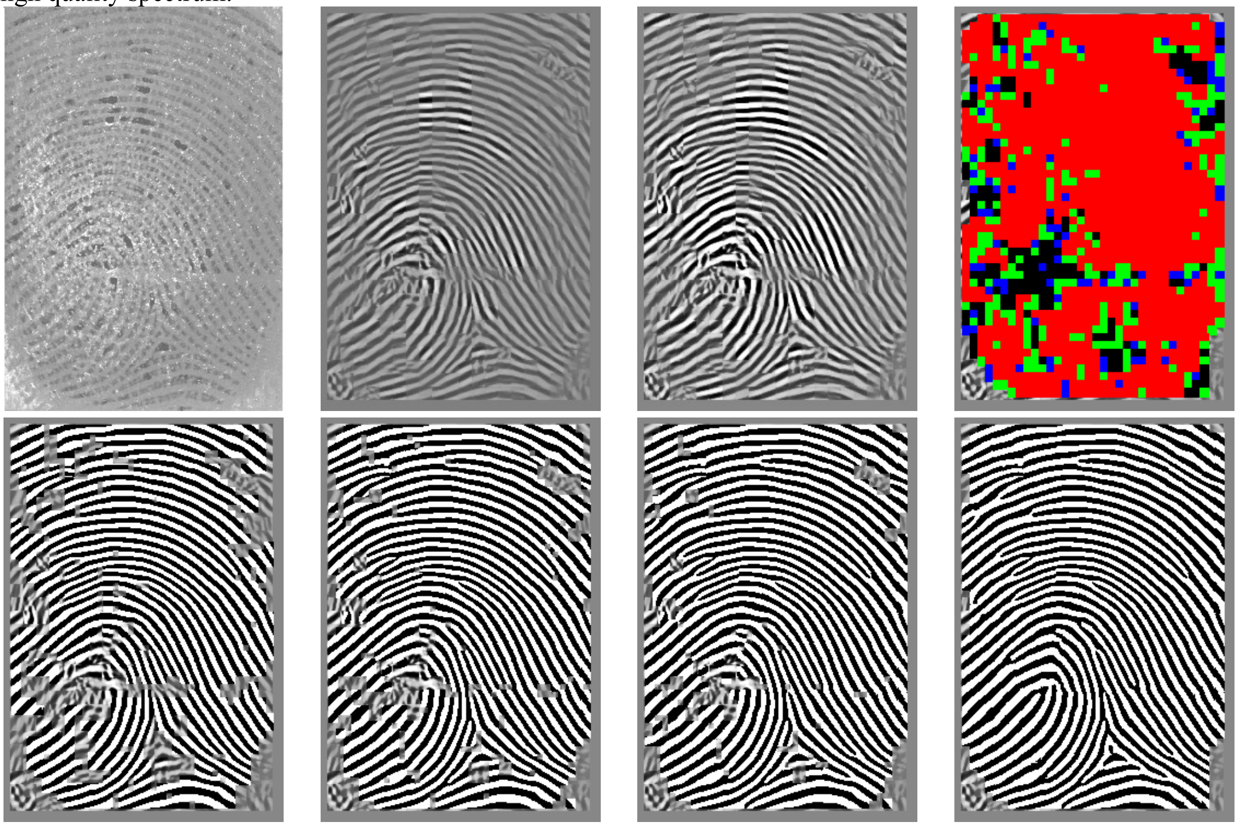


Fig.6. *The poor quality fingerprint image enhancement. The original fingerprint comes from 110_2 of FVC2000 DB2_B. The original input fingerprint image, Gabor filtering enhancement, LCS enhancement, the patches quality evaluation, iterating enhancement (High quality), iterating enhancement (Medium quality), iterating enhancement (Low quality) and the enhanced fingerprint image are shown in the figure from row 1 to row 2, from left to right, respectively.*

During fingerprint enhancement, the high quality patches are enhanced before the rest of patches with lower quality. We use a smaller size classification dictionaries to enhance the patches with high quality. In most fingerprint images, especially for the fingerprints enhanced with Gabor filtering, the regions with low quality are relatively small and most of the regions are with high quality. As a result, we can greatly reduce the calculation time while ensure the accuracy and reliability of the enhanced patches. What follows are to enhance the patches with lower quality using larger size classification dictionaries. The patches with higher priority are enhanced before the patches with lower priority. The multi-scale composite windows strategy makes sure that the patches with the lower quality have the composite window with the larger size. This can be a great way to improve the spectrum diffusion and reinforce the ability of the sparse representation based on dictionary learning for enhancing the patches with lower quality. Our algorithm fully take account of the contradiction between accuracy and noise tolerance, and greatly reduce the processing time.

An example of fingerprint enhancement via sparse representation over learned multi-scale classification dictionaries with reduced dimensionality is shown in Fig. 6. The high quality patches are first enhanced using the classification dictionaries with smaller sizes and dimensionality reduction based on the corresponding composite window, and then the inner patches of them are fed back into corresponding fingerprint image region, as shown in Fig. 6 row 2 column 1. The rest of lower quality patches are enhanced and fed to repeat the process by using dictionaries with a proper size and dimensionality reduction based on the corresponding composite window. The process is iterated until all patches have been enhanced, as shown in Fig. 6 row 2 column 4.

6. Experimental Results

To validate our proposed method on fingerprint enhancement performance, the performance of proposed algorithm is evaluation based on the public competition fingerprint databases FVC 2000 and FVC 2004. The comparative experimental results demonstrate that the proposed method is more effective and efficient in fingerprint image enhancement than the existing methods such as Gabor filter method [6], Chikkerur's STFT method [15], Sutthiwichaiporn's ABSF method [16], Ding's ACBF [17] method and Ding's CDL method [31].

6.1. The construction of multi-scale classification dictionaries with reduced dimensionality

In our proposed method, the fingerprint patches are enhanced by multi-scale composite windows. The size of the inner patch is set to 9×9 pixels, and the composite windows are defined by extending the inner patch to 17×17, 31×31 and 37×37 pixels, corresponding respectively to high, medium, and low qualities of the inner patches. The step-size of sliding window is 7 pixels. The corresponding multi-scale dictionary sizes are set to 289×289, 961×961 and 1369×1369. We select 500 high quality fingerprints from FVC 2000 and FVC 2004 to construct multi-scale classification dictionaries with reduced dimensionality training sample set. The fingerprints image in the selected training sample set are enhanced by using the open source software program VeriFinger Algorithm Demo (Publisher: Neurotechnology, https://www.directoryofshareware.com/preview/verifinger_algorithm_demo_for_ms_windows/). And then, the fingerprints are partitioned into various size patches to construct the multi-scale dictionaries training sets. The training patches with the same size are divided into 8 groups according to their own ridge orientation patterns. After sampling these patches, we select 50000 high quality patches from each class to build the classification dictionary training patches set. And then we transform all patches to frequency domain and the classification spectrum training sample sets are built. Finally, the multi-scale classification reduction dictionaries can be constructed using the method described in Section 4.2.

The size of the dictionary is critical for the computation performance of any enhancement method based on dictionary learning. Usually, the larger the dictionary the better the representation ability, however this comes with a higher computational cost. In the previous subsections we discussed the relationship between the patch enhancement and the patch size. In general, the anti-noise ability and the accuracy of an enhancement algorithm are mutually exclusive, and they both are closely related to the size of the patch: The larger the patch size, the better the anti-noise ability, however lower the enhanced accuracy it may lead to, and vice versa. Our solution to this issue is to enhance the fingerprint under the quality grading scheme. Under the scheme, we choose to enhance the higher quality patch (weak noise) using the dictionary with a smaller size. It can not only balance well between the accuracy and the anti-noise ability, but can also significantly reduce the computational complexity of fingerprint enhancement based dictionary learning, which is the double benefit of the scheme. In addition, we perform a dimensionality reduction to further save computations in the subsequent multi-scale classification dictionaries learning and fingerprint enhancement algorithms.

In Table 1, we report the results of dimensionality reduction over all classifications using each scale dictionary. According to the sizes of the dictionaries with reduced dimensionality in Table 1, we can find that the number of dimensions of the dictionaries can be significantly reduced by performing PCA dimension reduction operation. The computational complexity of each enhancement algorithm can be measured by its average execution time. The proposed method and the similar CDL method proposed in [31] are employed to enhance the fingerprints in FVC2000 DB1_B, and the corresponding execution times are shown in Fig. 7. As can be see directly, the proposed method greatly reduces the time required in enhancing the fingerprint image, mainly due to the use of the multi-scale dictionaries and the PCA for the dictionary dimensionality reduction.

6.1. Comparative experiments based on visual inspection

The proposed method has several advantages, ranging from dynamic dictionaries scale selecting, fingerprint ridge pattern preserving, and ridge spectrum diffusing. The use of multi-scale dictionaries ensures that the patches with various qualities can be enhanced by the dictionaries with proper sizes, which ensures the proposed method will perform much better in general. In addition, the proposed method is more reliable to preserve the ridges because the all patches are enhanced based on their own ridge pattern constraints. Moreover, the use of the spectrum diffusion based on multi-scale composite windows is helpful for improving the spectrum quality of low quality patches. In this subsection, we evaluate the performance of these algorithms from the perspective of visualization. The parameter of sparsity-constrained L is set to 3 in our experiments.

Table 1 Dimension Comparison of Different Scale Classification Dictionaries with Reduced Dimensionality

Dictionary size	The size of classification dictionaries with reduced dimensionality							
	i=1	i=2	i=3	i=4	i=5	i=6	i=7	i=8
289×289	44×289	72×289	60×289	70×289	52×289	67×289	56×289	69×289
961×961	142×961	239×961	198×961	238×961	169×961	230×961	184×961	230×961
1369×1369	208×1369	335×1369	284×1369	342×1369	240×1369	332×1369	267×1369	330×1369

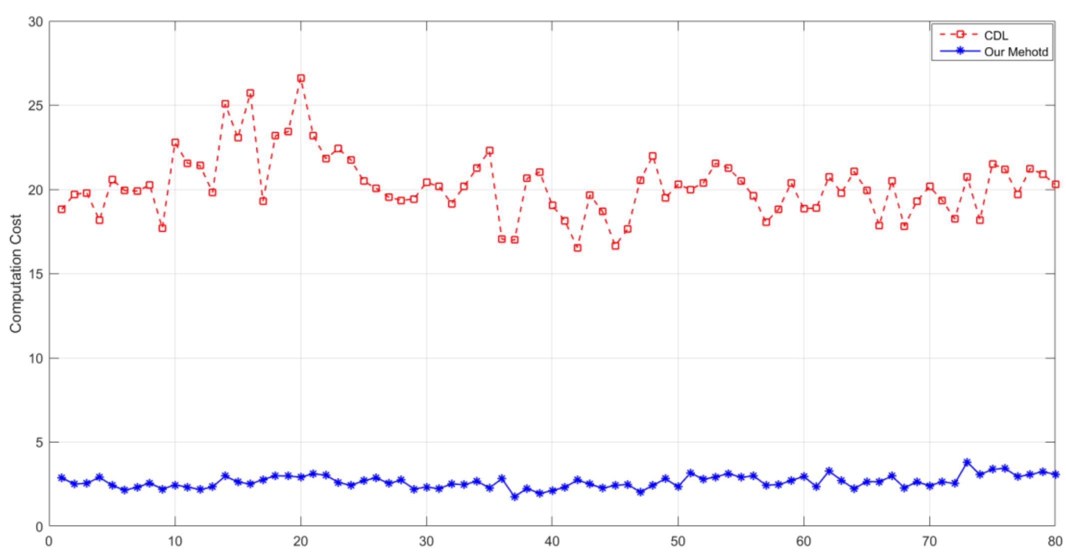


Fig. 7. *The comparison of the fingerprint enhancement computation cost using FVC2000 DB1 by the different methods. Number of images*

Fig.8. *Examples of fingerprint enhancement by proposed method. The original fingerprints come from FVC2000, DB1_B_106_1, DB2_B_104_2, DB2_B_108_6 and FVC2004, DB1_B_107_8 are shown in row 1. Correspondingly, row 2 show the enhanced fingerprints by the method proposed.*

Fig.9. *The fingerprints enhanced by various method, the original fingerprint image comes from FVC2004 DB2 4_8. The original fingerprint is shown in row 1 column 1. Correspondingly, the enhanced fingerprints by Gabor filtering method [6], STFT method [15], ABSF method [16], ACBF method [17], CDL method [31] and proposed method are shown from row 1 column 2 to row 2 column 3.*

Fig.10. *The fingerprints enhanced by various method, the original fingerprint image comes from FVC2004 DB2 16_8. The original fingerprint is shown in row 1 column 1. Correspondingly, the enhanced fingerprints by Gabor filtering method [6], STFT method [15], ABSF method [16], ACBF method [17], CDL method [31] and proposed method are shown from row 1 column 2 to row 2 column 3.*

As it can be seen in Fig. 8, proposed method has enhanced a wide range of low quality fingerprint images successfully. And then we conduct a series of experiments based on different algorithms to validate the robustness and efficacy of the proposed method, several results are shown in Fig. 9 and Fig. 10. From these figures, it can be seen that although the fingerprint ridges with weak noise can be enhanced well by various enhancement methods, they often fail to enhance the ridges with large noises. These fingerprints enhanced by our proposed method have achieved superior results with better visual inspection quality, for both ridge enhancement and noise suppression, which shows the proposed method is of a significant strength to balance and solve efficiently the conflict between ridge enhancement and noise suppression.

6.2. Fingerprint matching

In this subsection, we evaluate the performance of these algorithms from the perspective of fingerprint matching. It can illustrate the performance of various algorithms in AFIS for the purpose of getting a more accurate evaluation. We incorporate the enhancement scheme in the fingerprint identification system as a complete solution to assess the performance of our method in the entire fingerprint processing chain, from pre-processing, orientation field extraction, fingerprint enhancement and minutiae extraction to fingerprint matching. For minutiae-based fingerprint matchers, fingerprint enhancement is particularly important, because the matching reliability and robustness of the minutiae-based matcher are closely related with the accuracy of minutiae extraction which relies heavily on fingerprint enhancement.

The performance of AFIS can be evaluated by two indices: false match rate (FMR) and the false non-match rate (FNMR). In addition, in some cases the equal error rate (EER) also is used to evaluate the performance of AFIS. The lower the EER, the better the performance by the AFIS. We report the performance of various methods in terms of the evaluation indexes FMR, FNMR and EER. In real applications, the AFIS desires to far from the EER point by decreasing the FMR in order to assure a high level of security. However, decreasing the FMR will cause the FNMR to increase. It is therefore not surprising that the performance of an AFIS is often evaluated using the indicator FMR100, which is defined as the value of the FNMR when FMR is 1%.

In proposed method, we use an open source framework in C# (https://www.codeproject.com/Articles/97590/A-Framework-in-C-for-Fingerprint-Verification-2) for fingerprint matching and thus complete fingerprint identification. The matching algorithm that is employed in our experiments is based on minutia triplets [41], named M3gl. It should be noted that the fingerprint matching process is fixed except for the specific enhancement algorithm in this experiment. In order to show the differences of various enhancement methods, we did the experiments on the FVC2000 DB1_B, DB2_B, and DB4_B respectively.

The ROC curves for the six algorithms are shown in Fig. 11. They illustrates the performance of various methods, respectively. Compared with other similar algorithms, the proposed method shows a much better performance in terms of EERs, it provides a lower FMR100s in most cases. This is attributed to a combination of the use of the multi-scale classification dictionaries and the spectrum diffusion based on multi-scale composite windows. The proposed method effectively enhances the input fingerprint and improves reliability and accuracy of minutiae extraction and matching, as can be seen from the EERs and FMR100s listed in Table 2 for all algorithms. From Table 2, we can see that proposed method improves the accuracy of the equal error rates of Gabor filter by about 61%, 78% and 65% on FVC2000 DB1_B, DB2_B and DB4_B respectively. Furthermore, proposed method improves the accuracy of the FMR100s of Gabor filter by about 63%, 80% and 70% on FVC2000 DB1_B, DB2_B and DB4_B respectively. Experimental results show that the performance of AFIS is greatly improved when the input fingerprint images are enhanced using proposed method.

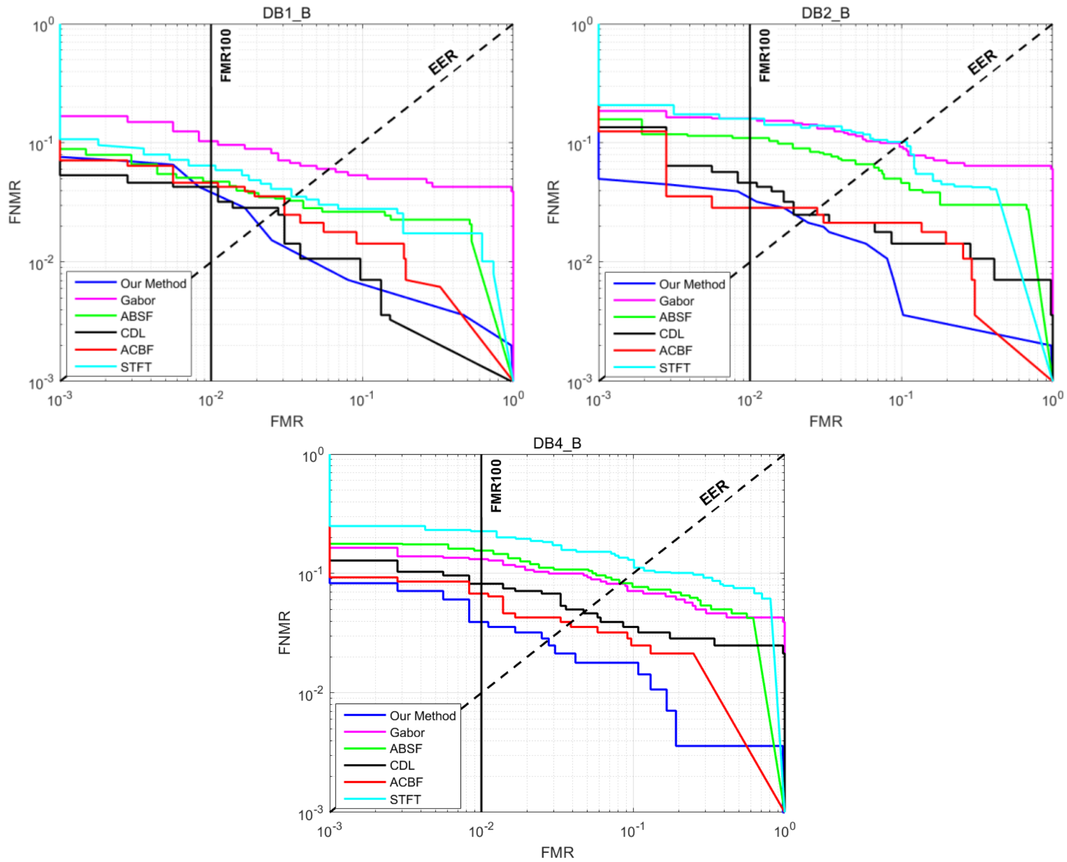


Fig.11. *ROC curves of different fingerprint enhanced by different methods on FVC2000 databases.*

Table 2 Performance Comparison of Different Enhancement Algorithms on FVC2000 DB1_B, DB2_B and DB4_B

Fingerprint		Our Method	Gabor_En [6]	ABSF[16]	CDL [31]	ACBF [17]	STFT [15]
DB1_B	EER(%)	**2.150**	5.536	3.276	2.639	2.778	3.548
	FMR100(%)	**3.850**	10.357	5.109	4.286	4.643	6.469
DB2_B	EER(%)	**2.105**	9.504	6.630	2.222	2.639	10.200
	FMR100(%)	3.214	16.071	10.235	4.643	**2.857**	15.998
DB4_B	EER(%)	**2.639**	7.440	8.288	4.683	3.730	11.179
	FMR100(%)	**3.929**	13.214	15.156	8.214	6.786	22.626

*The minimum EER or FMR100 in each row is bolded.

7. Conclusion

In this paper, an effective fingerprint enhancement algorithm using sparse representation over learned multi-scale classification dictionaries with reduced dimensionality has been proposed. In order to balance the contradiction between the anti-noise ability and accuracy while reducing the processing time complexity, a multi-scale windows-based scheme is proposed. The goal is achieved under the quality grading scheme combined with the multi-scale composite windows strategy. To reduce the computational complexity and improve the computational efficiency, PCA is introduced into the scheme to reduce the dimensionality of dictionary used in training and enhancing. With the proposed algorithm, training samples are classified into eight groups according to ridge orientations. The use of the classification dictionaries created based on ridge patterns improves the effectiveness of sparse modeling of information in a fingerprint patch. By assessing the quality of a given patch, the patches with higher quality are firstly enhanced by the dictionary with smaller sizes, which is essential for generating a high quality enhancement while keeping the time complexity low. The combination of quality assessment and the multi-scale composite windows promises to ensure that spectra diffusion is successfully applied. The proposed algorithm can evidently improve the quality of fingerprint and obtain better identification performance.

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