Fusing 3D Gabor and Block-wise spatial Features for Hyperspectral Palmprint Recognition

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Abstract. Hyperspectral palmprint contains various information in the joint spatial-spectral domain. One crucial task in hyperspectral palmprint recognition is how to extract spatial-spectral features. Since hyperspectral palmprint is three dimensional, most of the existing 2D based algorithms, such as collaborative representation (CR) based framework [15], may not fully explore the information on the spectral domain. Although 3D Gabor filter [20] can be utilized to encode the information on the joint spatial-spectral domain, the texture direction information such as the surface map may not be explored sufficiently. In this work, a novel response-competition (ResCom) feature is proposed to present the spectral information of hyperspectral palmprint based on 3D Gabor filters. Incorporated with the 2D surface map, the ResCom feature can encode not only the 2D texture but also the 3D response variation. Therefore, features of hyperspectral palmprint will be extracted efficiently on the joint spatial-spectral domain. By fusing Block-wise and ResCom features, the proposed approach achieves so far the highest recognition rate of 99.43% on the public hyperspectral palmprint database.

Keywords: 3D Gabor · hyperspectral palmprint · fusion feature

1 Introduction

Due to its similarity with the stimulation function of visual cortex cells, Gabor wavelets have been widely used in extracting features for biometrics like face and palmprint [1]. Coding-based approaches firstly apply a set of Gabor wavelets to extract local features, and then encode the responses of wavelets to a binary code for fast matching. PalmCode [2], CompCode (Competitive Code) [3] and FusionCode [4] are three examples of them. Palmcode used a finely tuned Gabor wavelet to extract the orientation and width information of the lines in the palmprint. CompCode encodes the winning wavelet's index, and FusionCode encodes the resulting wavelet's response. The experimental results of the two methods are superior to the PalmCode. The direction filters are typically used

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by line-based systems to represent the orientation information of principal lines and wrinkles.

Recently, multispectral imaging with different illumination sources has attracted lots of research attention due to its advantages in accuracy and anti-spoofing for biometrics applications. An empirical study by Guo et al [5] made a conclusion that different illumination sources include yellow or magenta are the best spectral bands for palmprint recognition. Since then, Multispectral Palmprint recognition systems using the images captured by red, blue, green and Near Infrared light sources [7–9] have been developed. In [6], a hyperspectral imaging device was developed to capture the palmprint images at 69 spectral bands over spectrum 420-110nm with a step of 10nm. Hyperspectral palmprint contains various information on the joint spatial-spectral domain. It is an important and challenging topic to encode the features of these palmprints effectively.

A common practice is to process and identify the 2D images on each band, and then combine the results for the final decision [10]. However, a better strategy is to extract feature on the joint spatial and spectral domain using three-dimensional filters directly, such as 3D Gabor wavelets. The filters have been successfully applied on both hyperspectral palmprint recognition [11] and hyperspectral face recognition [12]. Shen et al. [11] exploited the information that contained in the hypercube data. A set of 3D Gabor wavelets were convolved with the cube data to jointly extract signal variances on spatial and spectral domains. But the dimension of the feature is very high [13], which could cause curse of dimensionality. To avoid this situation, they proposed an Affinity Propagation (AP) based method [14] to cluster the 2D bands of hyperspectral palmprint data. Then the redundant bands could be removed and 3D Gabor wavelets were convolved with the remaining bands only. Therefore, the feature size can be significantly reduced, and the efficiency can be greatly improved. Collaborative representation(CR) based framework with $l_2 - norm$ has been used on depth maps of palmprint due to its ability to robustly classify pixels by curvature and Gaussian curvature [19]. However, CR based framework has not been explored for the hyperspectral palmprint recognition.

In this paper, we propose a novel local feature named response-competition (ResCom) feature, to utilize the magnitude and phase of the maximum 3D Gabor response sufficiently. The feature vectors encoded by the look-up table imply the surface geometry characteristics. In addition to the proposed local features, this paper also combines ResCom feature with the information of the 2D images on each band. Moreover, the ResCom feature and CR Based framework with $l_2 - norm$ regularization[15] are combined to improve the recognition accuracy.

This paper is structured into the following sections. The proposed framework of palmprint recognition is presented in Section 2. Then the experimental results and the corresponding illustrations are demonstrated in Section 3. Finally, the conclusion and some discussions are presented in Section 4.

2 Framework of the Algorithm

2.1 3D Gabor Wavelets

The Gabor function [12] is proposed to maximize the resolution of the joint time and frequency of the signal, which is modulated by the sine function of Gaussian. Granlund first introduced the Gabor elementary functions to the 2D counterpart. Since then, 2D Gabor wavelet [13] is widely used to solve various visual problems, including feature extraction, texture classification [18, 19], palmprint recognition [2] and face recognition [12]. With the extensive applications of 2D Gabor wavelets, 3D Gabor wavelets have also been utilized on 3D brain image registration, hyperspectral image classification and face recognition.

In the 3D frequency domain (u, v, w), if we represent the angle between the frequency vector f and the w axis as φ, the angle between f and uv plane as θ, 3D Gabor wavelet (x, y, b) can be defined as follows [1]:

$$\begin{cases} \Psi_{f,\varphi,\theta}(x,y,b) = S \times exp(-((\frac{x'}{\sigma_x})^2 + (\frac{y'}{\sigma_y})^2 + (\frac{b'}{\sigma_b})^2)) \\ \qquad\qquad\qquad\qquad \times exp(2\pi j(xu + yv + bw)) \\ u = f \sin\varphi \cos\theta, v = f \sin\varphi \sin\theta, w = f \cos\varphi \\ [x', y', b'] = R \times [x - x_c, y - y_c, b - b_c]^T \end{cases} \tag{1}$$

where S is scale, (x_c, y_c, b_c) denote volume element coordinate, f is the central frequency of the sinusoidal plane wave, φ and θ are the angles of the wave vector with w axis and $u - v$ plane in frequency domain (u, v, w), R is the rotation matrix, and $\sigma_x, \sigma_y, \sigma_b$ are the widths of Gaussian envelops in different axis. For representing the local information about various frequencies and orientations, a set of $I \times J \times K$ Gabor wavelets with different frequencies are introduced to extract features from volume data:

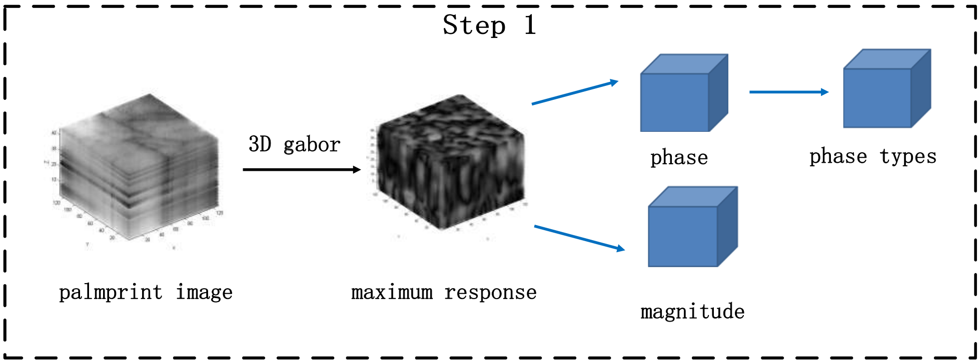
$$\{\Psi_{i,j,k} \triangleq \Psi_{f_i,\varphi_j,\theta_k}(x,y,b), f_i = f_{max}/2^i, \varphi_j = j\pi/J, \theta_k = k\pi/K\} \tag{2}$$

where f_i, (φ_j, θ_k) define the amplitude and orientations of central frequency, f_{max} is the highest possible amplitude of frequency.

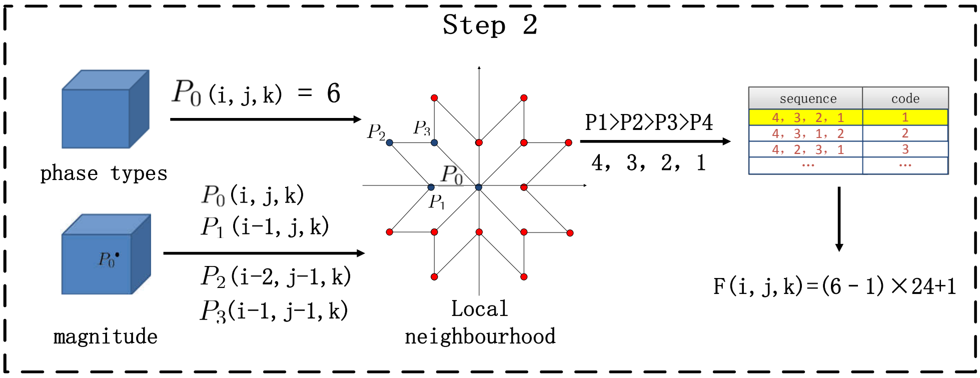
Given a set of 3D Gabor wavelets $\{\Psi_l, l = 1, \cdots, L\}$ and a hyperspectral palmprint image $V(x, y, b)$, the convolution coefficient $V \otimes \Psi_l(x, y, b)$. response to the phase $P_l(x, y, b)$, the wavelet index m and the magnitude $M_l(x, y, b)$ of the position (x, y, b) are defined as follows:

$$\begin{cases} P_l(x,y,b) = arg\tan(\frac{Im(V \otimes \Psi_l(x,y,b))}{Re(V \otimes \Psi_l(x,y,b))}) \\ m = arg\max_l M_l(x,y,b) \\ M_l(x,y,b) = |V \otimes \Psi_l(x,y,b)| \end{cases} \tag{3}$$

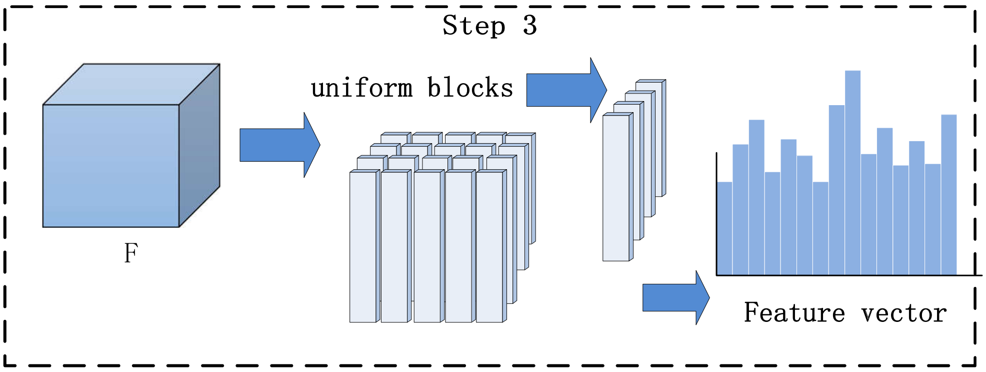
where the $| \otimes |$ operation extracts the size of the convolution coefficient, and the Im and Re operations are the imaginary and real parts of the complex coefficients, respectively.



(a) Magnitude and phase types.



(b) Encode the pixels according to the corresponding phase types.



(c) Local histograms.

Fig. 1: The process of feature extraction.

2.2 The Proposed Feature

ResCom feature is the local feature extracted by the maximum response of Gabor wavelet. We produce a new cube from phase and magnitude of the response, that has the same size as the sample data. The cube is then divided into uniform blocks. And the histogram of each block is extracted to form the feature vector. As shown in Fig.1, the feature extraction is conducted by the following steps:

- Calculate the magnitude and phase. The magnitude and phase as described in Eq. (3) can be generate from the real and imaginary parts of the maximum response produced by the 3D Gabor wavelet. As shown in Fig. 1(a), the magnitude cube and phase types cube are both with size $M \times N \times B$, where $M = 64$, $N = 64$, $B = 54$. As defined in (4), the phase values are classified into nine types.
- Encode the pixels according to the phase types. The local neighborhoods of each point in magnitude cube are divided into eight sectors as shown in Fig. 2. In other words, the sector which we choose to encode is decided by corresponding phase types. Then the sector is chosen and find the four pointsP_0,P_1,P_2,P_3 are found. The value at P_0,P_1,P_2 and P_3 are ranked to produce the sequence of 1-4. For example, as shown in Fig. 1(b), P_0 in phase types cube is 6 and then the sixth sector is chosen. A sequence of "4,3,2,1" is used to represent the relationship of P_3,P_2,P_1,P_0. The full permutation of 1-4 by a lookup table is stored as shown in Fig. 1(b) and the sequence is mapped to the code according to the table. At last we can get code = 1 in this example. Then the initial feature information F is obtained by size $M \times N \times B$, according to Eq. (4).
- Compute local histograms of F. We divide F into $P \times P$ blocks and use local histograms as features, P=16 in this paper. The size of each feature vector is $P \times P \times K$, where K=193.

$$\text{PhaseTypes(i,j,k)} = \begin{cases} 9 & \text{if } Mag \leq 1e-6 \\ \lfloor \frac{\theta}{SpanAng} \rfloor + 1 & otherwise \end{cases} \tag{4}$$

where θ is angle value, SpanAng denotes the step size (45° in this paper, see Fig. 2 for details) and $\lfloor \cdot \rfloor$ denotes the floor operation.

$$\text{F(i,j,k)} = \begin{cases} \text{(PhaseTypes-1)} \times 24 + code & \text{if } 1 \leq K \leq 8 \\ 193 & \text{if } K = 9 \end{cases} \tag{5}$$

where code is value listed in the look-up table based on the sequence.

2.3 L2-norm Recognition Framework

After the feature extraction, we combine ResCom and Block-wise feature in the $L2-norm$ recognition framework. In [15], Block-Wise features performed

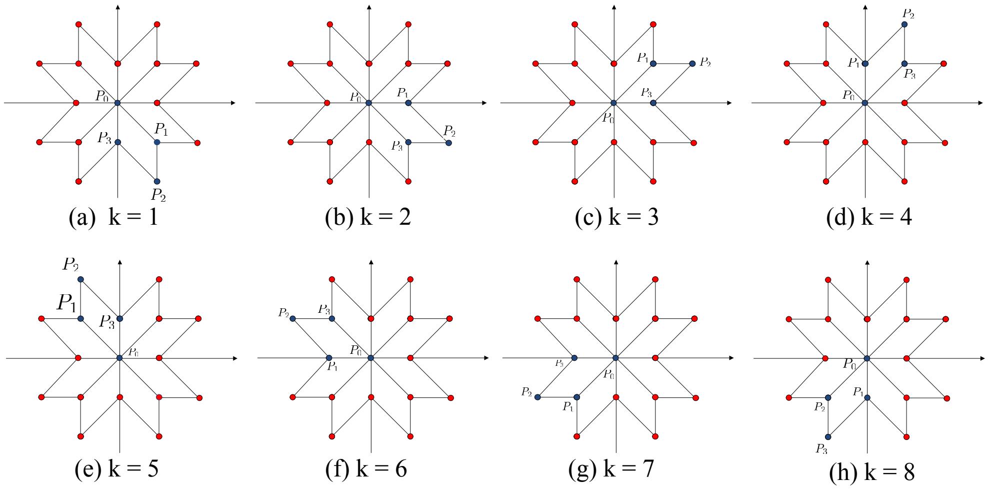


Fig. 2: Eight sectors of neighbourhood.

palmprint recognition based on the signs of the mean curvature H and Gaussian curvature K in equation (6).

$$\begin{cases} H = \frac{(1+f_x^2)f_{yy}+(1+f_y^2)f_{xx}-2f_xf_yf_{xy}}{2(1+f_x^2+f_y^2)^{3/2}} \\ K = \frac{f_{xx}f_{yy}-f_{xy}^2}{(1+f_x^2+f_y^2)^2} \end{cases} \tag{6}$$

where f_x, f_{xx} are the first and second order partial derivatives in the x-direction. f_y, f_y are the first and second order partial derivatives in the y-direction.

See Table 1 for detailed information of our algorithm.

3 Experimental Results

3.1 Database

The proposed method is tested using the HK-PolyU hyperspectral palmprint Database [9]. As shown in Fig. 3, the hyperspectral palmprint images were captured under wavelengths from 420nm to 1100nm. The samples were collected from 190 volunteers whose ages are from 20 to 60 years old. Each palm was captured at 69 spectral bands with a step-length of 10nm over spectrum 420nm-1100nm. In total, the database contains 5,240 images from 380 different palms. After preprocessing, each image is cropped into an ROI of size $M \times N$ pixels. Fig. 3 shows six bands of an example palm, and the third dimension (z-axis) is the magnitude of wavelengths.The 1st and 2nd sessions of palmprint database are used as the gallery and probe sets, respectively.

Table 1: L2-norm Recognition Framework

Training phase:
Input: A gallery set containing hyperspectral palmprint.
Output: The dictionary matrix M.
1, For each sample in the gallery set
Extract the ResCom vector g;
Divide the sample into $P \times P$ patches on each band, where each block contains $Q \times Q = P$ pixels, where Q=4, P=16, then B blocks are obtained for B spectral bands.Extract from these blocks a Block-Wise feature vector h;
Combine g and h to form feature vector b and Normalize b to have unit $l_2 - norm$
2, Concatenate all bs as M.
Testing phase:
Input: A query hyperspectral palmprint samples and M.
Output: Identity of the query sample.
1, For each sample in the query set
Extract the ResCom feature vector l;
Extract the Block-Wise feature vector r;
Combine l and r to form feature vector y and Normalize y to have unit $l_2 - norm$
2, Code y over A as:
$w_0 = argmin_w\{||y - Dw||_2^2 + \lambda_1||w||_2^2\}$.
3, Compute the residuals $r_i(y) = ||y - A\delta_i(w_0)||_2$ where $\delta_i(w_0)$ is a new vector whose only nonzero entries are the entries in w_0 that are associated with class i.
4, Find the label according to $id(y) = argmin_i r_i(y)$.

Table 2: Experimental Results

Employed feature	Recognition Rate
Gabor maximum response	0.9719
Block-wise	0.9928
Gabor ResCom	0.9863
Block-wise + Gabor maximum response	0.9932
Block-wise + Gabor ResCom	**0.9943**

3.2 Results

The recognition rates of different features are summarized in Table 2. In Gabor ResCom feature, each quadrant in equation (5) is divided into two sectors according to the phase. From the above, this proposed feature can combine the phase and magnitude information and make feature vectors more discriminative. Using the Gabor ResCom feature, the recognition rate can reach 98.63%.

In addition to the Gabor ResCom feature, we combine ResCom feature with block-wise extracted on each band. Consider CR Based Framework with $l_2 - norm$ Regularization(Block-wise) [15], the recognition rate on hyperspectral palmprint database is 99.32%, where the curvature features on the faces $x - y$, $x - z$ and $y - z$ are extracted. In our work, The fusion of block-wise feature and ResCom achieved the accuracy of 99.43%.

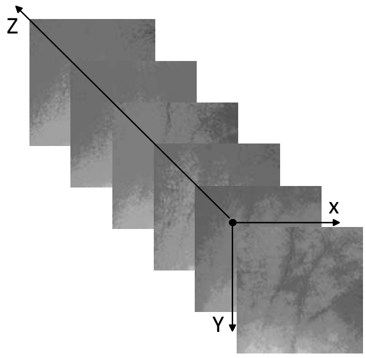


Fig. 3: A hyperspectral palmprint sample.

4 Discussion and Conclusion

In this paper, a novel feature encoding method based on 3D Gabor wavelets is proposed for the hyperspectral palmprint recognition. The fused feature based on 3d Gabor wavelets is extracted to improve the accuracy of CR framework for hyperspectral palmprint recognition. The experimental result indicates that the CR framework can exhibit good performance for hyperspectral palmprint after combining the local information from maximum response produced by 3d Gabor filtering. Although competitive results are obtained with the proposed feature, there is still room for further improvement. More efficient features respresenting the 3D geometry characteristics should be devised and integrated. Finally, feature selection will be explored in our future work.

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