On The Power of Joint Wavelet-DCT Features for Multispectral Palmprint Recognition

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Abstract—Biometric based identification has drawn a lot of attention in the recent years. Among all biometries, palmprint is known to possess a rich set of features including geometrical and textural features, lines, corners and so on. Therefore, the features that can be used to pinpoint a single palmprint are many, but it is important to choose the combination of the most distinguishing features to minimize the calculations and maximize efficiency. In this paper we proposed to use DCT-based features in parallel with wavelet-based ones for palmprint identification. Then these features are used to match palmprints using the majority voting algorithm (MV). The features introduced here are very simple to compute and result in extremely highly accurate identification. This method is tested on a well-known multispectral palmprint database and an accuracy rate of 99.97-100% is achieved which beats all previous methods under the same scenario.

I. INTRODUCTION

To personalize an experience or make an application more secure and less accessible to the undesired people, we need to be able to distinguish a person from everyone else. It is done using marks from the users to identify them and allow only the authorized or change it according to the identity of the client. To do so, many alternatives are on the table, such as keys, passwords, cards and so on. The most secure options, however, are those which cannot be imitated by any other than the desired person himself. Called biometric features, they are divided into behavioral features that the person can uniquely create or express, such as signatures or walking rhythm, and physiological characteristics that the person possesses, such as fingerprints and iris pattern. Many works revolve around identification, verification and categorization of such data including but not limited to fingerprints [1], palmprints [2], faces [3] and iris patterns [4].

In many identification systems, there is a database of the people whose multiple desired samples are written inside. To identify, the device takes a sample of the entry, extracts its features and compares them to the database entries. Usually there is a threshold present that should the acquired data fail to cross, the input will be deemed as false. This happens when the person whose sample is being taken is not in the database at all. However, if the person is present in the source, the program finds the closest match and allows the person to use the protected service. At the same time, the authorization is recorded for security purposes and in some cases, even the new sample might replace one of the old ones for the same process in the future.

To use palmprints as an identification factor, two widespread methods exist; either transforming the images into another domain like Fourier, DCT, wavelet or Gabor, or attempting to extract the lines and the geometrical characteristics from the palms. Many transform-based approaches exist, such as [5], in which Zeng utilized a two-dimensional Gabor-based features and a nearest neighbor classifier for palmprint recognition, [6] in which Wu presented a wavelet-based approach for palmprint recognition and used wavelet energy distribution as a discriminant for the recognition process and [7] where Badrinath used DCT and Hamming distance for palmprint recognition and enhanced it by correcting the light non-uniformity in the palm images, especially the low-resolution ones. Among notable line-based approaches is [8] where Cook proposed an automated flexion crease identification algorithm using image seams and kd-tree nearest neighbor searching that has a very high accuracy.

Recently in the area of multispectral palmprint recognition, the work presented in [9] by Xu involves a quaternar principal component analysis approach for multispectral palmprint recognition with a high accuracy. In [10], Mistani proposed to use a set of hybrid spatial and frequency-based features followed by a minimum distance classifier algorithm to perform identification task. The work in [11] by Minaee introduces a recognition algorithm based on a set of features consisting of statistical features derived from spatial domain and wavelet domain features which results in a very high accuracy rate. Also in [12], Minaee proposed a set of textural features derived from the co-occurrence matrix of palmprints and with the use of majority voting, achieved a highly accurate identification.

Most of the palmprint recognition systems consist of four general steps: image acquisition, preprocessing, feature extraction and template matching. These steps are shown in the following block diagram:

![Image](https://via.placeholder.com/150)

Fig. 1. Block diagram of general biometric recognition system

Images can be acquired by different devices, such as CCD cameras, digital cameras and scanners. In our work, we have used the multispectral palmprint database which is provided by Polytechnic University of Hong Kong [13] and contains 12 palmprint samples from 500 different palms [20]. Images
are acquired using four CCD cameras to take four images from each palmprint under four distinct light spectra: blue, green, NIR and red. In the preprocessing steps, images are usually aligned and the region of interests (ROI) are extracted for all palms. The alignment process can be performed using the key points. In PolyU multispectral dataset, all images are preprocessed. Different spectra for a sample palmprint of this dataset are shown in Figure 2.

![Image](image_url)

**Fig. 2.** Blue, Green, NIR and Red spectrums of a palmprint

In the feature extraction step, a set of 18 features is proposed: 9 DCT-based features and 9 wavelet-based features. In spite of the simplicity of these features, they result in a very high accuracy rate. After feature extraction, we used the majority voting scheme to match and identify palmprints.

The rest of the paper is organized as follows. Section II describes the proposed set of features. Section III contains an explanation of our classification technique. Results of our experiments and comparisons with other works are in Section IV and the conclusion is in Section V.

## II. Features

Feature extraction is one of the most essential steps in machine learning and data analysis and the information features provide is correlated with the accuracy of the algorithm. Highly discriminating features usually have a large variance across different classes of target values and a small variance across samples of each class. The optimum features for two different tasks could be entirely different. There different approaches for feature extraction [14]. One approach is to attempt to automatically derive the useful set of features from a set of training data such as PCA and ICA. The other approach is to intuitively design a set of features based on the characteristics of data, such as wavelet-domain features and HOG (Histogram of Oriented Gradients).

In the palmprint recognition area, the most widely used features include statistical features, textural features, line features, hand geometry features and point features. Statistical and textural features are the most widely used since they are easier to extract and they are robust to noise. Wavelet and Gabor domain features are specific cases of transform domain features. Line features derived from principle lines and wrinkles are also very popular, but are difficult to extract because detecting the principle line could be a challenging task, especially in the presence of noise or low-resolution images. Geometrical features are those features pertaining to the shape and pattern of the hand such as the area of palmprint and its width and length. Geometrical features have been used in various domains of medical image analysis such as medical image segmentation where one can use the geometrical characteristics of an object to segment it from other objects [15].

Here a combined set of DCT- and wavelet-based features is used to perform multispectral palmprint identification. These features are extracted from small patches of each image and subsequently, features of different patches are concatenated to form total feature matrix of each image. Based on the simulations, these features result in a very accurate identification method for multispectral palmprints.

### A. DCT Domain Features

Discrete cosine transform has a lot of applications in various areas of image processing including image compression and image denoising [17]. Because of its energy compaction property, most of the image information tends to be concentrated in a few DCT coefficients and makes it favorable for image compression applications. DCT approaches Karhunen-Loeve transform of images under mild assumptions.

Suppose we have a 2-dimensional discrete function \( f(m,n) \) of size \( M \times N \), then the 2-D DCT of that function can be defined as:

\[
F(u,v) = \alpha_u \alpha_v \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f(m,n) \cos \left( \frac{(2m+1)u}{2M} \right) \cos \left( \frac{(2n+1)v}{2N} \right)
\]

where \( 0 \leq u < M - 1 \) and \( 0 \leq v < N - 1 \) and:

\[
\alpha_u = \begin{cases} 
\sqrt{1/M} & \text{if } u = 0, \\
\sqrt{2/M} & \text{otherwise}.
\end{cases}
\]

\[
\alpha_v = \begin{cases} 
\sqrt{1/N} & \text{if } v = 0, \\
\sqrt{2/N} & \text{otherwise}.
\end{cases}
\]

To extract DCT features from palmprints, every palmprint is divided into non-overlapping blocks of size 16×16 and the 2D DCT of each block is computed. Then, the first 9 DCT coefficients in the zig-zag order are selected as DCT features. These features are shown in the following matrix.

\[
\begin{bmatrix}
  f_0 & f_1 & f_5 & f_6 & \cdots \\
  f_2 & f_4 & f_7 & \cdots \\
  f_3 & f_8 & \cdots \\
  \vdots & & & & 16 \times 16
\end{bmatrix}
\]

Note that the zero frequency coefficient \( (f_0) \) will not be used due to it being the same as the mean value of intensities.

One can also keep more than 9 DCT coefficients or can also make use of all DCT coefficients. But based on our implementation using the first 9 coefficients achieves a high accuracy rate for multispectral palmprint recognition.
B. Wavelet Domain Features

Wavelet is a very popular tool for a variety of signal processing applications such as signal denoising, signal recovery and image compression [18]. Perhaps JPEG2000 is one of the most notable examples of wavelet application [19]. In our feature extraction procedure, the images are first divided into $16 \times 16$ non-overlapping blocks and then the 2D-wavelet decomposition is performed up to three stages and in the end 10 sub-bands are produced. The energy of wavelet coefficients in these subbands are used as the wavelet features (the LL subband of last stage is not used here). The summary of our wavelet feature extraction in presented in the following algorithm:

1) Divide each palm image into $16 \times 16$ non-overlapping blocks;
2) Decompose each block up to 3 levels using Haar wavelet transform; and
3) Compute the energy of each subband and treat it as a feature.

An example of 3-level wavelet decomposition of a palmprint is presented in Figure 3.

![Image](Image 77x368 to 272x466)

Fig. 3. Left: A palm image, Right: 3-level wavelet decomposition of the image

After computation, there will be a total of 18 different features ($9 \text{ DCT}+9 \text{ Wavelet}$) for each block which can be combined in a vector together: $\mathbf{f} = (f_1, f_2, \ldots, f_{18})^T$. It is necessary to find the mentioned features for each block of a palmprint. If each palm image has a size of $s_1 \times s_2$, the total number of non-overlapping blocks of size $16 \times 16$ will be:

$$M = \frac{s_1 \times s_2}{16^2}$$

Therefore, there are $M$ such feature vectors, $\mathbf{f}^{(m)}$. Similarly, they can be put in the columns of a 2-dimensional matrix to produce the feature matrix of that palmprint, $\mathbf{F}$:

$$\mathbf{F} = [\mathbf{f}^{(1)} \mathbf{f}^{(2)} \ldots \mathbf{f}^{(M)}]$$

There are totally 18M features for each palmprint image.

III. CLASSIFIER: MAJORITY VOTING

After the features are extracted a classifier is required to match the most similar image in the data set to the test subject. There are different classification algorithm that can be used. Some of the most widely used include minimum distance classifier, neural network, support vector machine and majority voting. These algorithms usually have some parameters which need to be tuned. The parameter tuning is usually done by minimizing a cost function on the training set. If the dataset is large enough, the cost function is basically the training error. But if the data set is small, the cost function should have two terms; one term tries to minimize the error; and the other term tries to minimize the risk of over-fitting. One such work is presented in [19].

Here we have used majority voting algorithm. It is done by individual prediction by every feature followed by adding all the votes to determine the outcome. One can also use weighted majority voting algorithm where each feature is given a weight in the voting process. The weights of each feature are usually related to the single feature accuracy in classification task; the more it can predict on its own successfully, the greater weight it is given. Here we have given uniform weight to all features to make the algorithm parameters independent of the dataset.

In our classifier, first the training images’ features are extracted. Then, the features of test sample are extracted and the algorithm searches for a training image which has the minimum distance from the test image. Each time one feature is used to select a training sample with the minimum distance and that sample is given one unit of score and this procedure is used to select a training sample with the minimum distance from the test image. Each time one feature is used to select a training sample with the minimum distance and that sample is given one unit of score and this procedure is repeated for all features. In the end, the training sample with the highest score is selected as the most similar sample to the test subject.

Let us denote the $i$-th feature of the test sample by $f_i^{(t)}$, the predicted match for the test sample using this feature will be:

$$k^*(i) = \arg\min_k ||f_i^{(t)} - f_i^{(k)}||^2$$

where $f_i^{(k)}$ is $i$-th feature of the $k$-th person in the training data.

Let us denote the score of the $j$-th person based on $f_i$ by $S_j(i)$ and $S_j(i) = \mathbf{I}(j = \arg\min_k ||f_i^{(t)} - f_i^{(k)}||)$, where $\mathbf{I}(x)$ denotes the indicator function. Then the total score of the $j$-th training sample using all the spectra is found by the following formula:

$$S_j = \sum_{\text{All spectra}} \sum_{i=1}^{i_{\text{max}}} \mathbf{I}(j = \arg\min_k ||f_i^{(t)} - f_i^{(k)}||)$$

Finishing the calculations, $j^*$ or the matched training sample will be:

$$j^* = \arg\max_j \left[ S_j \right] = \arg\max_j \left[ \sum_{\text{All spectra}} \sum_i S_j(i) \right]$$

IV. RESULTS

We have employed the algorithm suggested in this paper on the PolyU multispectral palmprint database [20] which has 6000 palmprints sampled from 500 persons. Each palmprint is taken under 4 different lights in two days, is preprocessed and has a size of $128 \times 128$.

We have studied the palmprint recognition task for three different sets of features: DCT features, wavelet features and
Joint wavelet-DCT features. We have performed palmprint identification for every case using different number of training and testing data. When an image is matched to the test subject incorrectly, it is called a mis-identification or failure.

The accuracy rate of the proposed method using different feature sets are presented in Table I.

### Table I

**ACCURACY RATE FOR DIFFERENT FEATURE SETS**

| Training sample fraction | DCT features | Wavelet features | DCT+Wavelet features |
|--------------------------|--------------|-----------------|---------------------|
| 4/12                     | 99.8%        | 99.87%          | 99.97%              |
| 5/12                     | 99.8%        | 99.89%          | 100%                |
| 6/12                     | 99.9%        | 99.97%          | 100%                |

Figure 4 illustrates the accuracy rates from Table I. As we can see wavelet features have a slight advantage over DCT features. By combining these two sets of features, we are able to get the highest accuracy.

The experiment has been performed using MATLAB on a laptop with Windows 8 and Core i5 CPU running at 2.6GHz. The execution time for the proposed method is about 0.1s, 0.11s and 0.2s per test using DCT, wavelet and joint wavelet-DCT features respectively. As a result, the proposed algorithm can be performed in real-time systems.

### V. Conclusion

This paper proposed a set of joint wavelet-DCT features for palmprint recognition. These features are extracted from non-overlapping sub-images so that they capture the local information of palmprints. These features are sensitive to the small differences between different palmprints. Therefore they are able to discriminate different palms with very similar patterns. The proposed algorithm has significant advantages over the previous popular approaches. The proposed features here are very simple to extract. The algorithm is very fast and it does not need a lot of calculations. Most importantly, it has a very high accuracy rate which is robust to the number of training samples and can be high even for the case where the ratio of training to test is 1 to 2.

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