Highly Accurate Multispectral Palmprint Recognition Using Statistical and Wavelet Features

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Abstract—Palmprint is one of the most useful physiological biometrics that can be used as a powerful means in personal recognition systems. The major features of the palmprints are palm lines, wrinkles and ridges, and many approaches use them in different ways towards solving the palmprint recognition problem. Here we proposed to use a set of statistical and wavelet-based features; statistical to capture the general characteristics of palmprints; and wavelet-based to capture those information which are not evident in the spatial domain. Subsequently we use two different classification approaches, minimum distance classifier (MDC) scheme and weighted majority voting algorithm (WMV), to perform palmprint recognition. The proposed method is tested on a well-known palmprint dataset of 6000 samples and shows an impressive accuracy rate of 99.65%-100% for most scenarios.

Index Terms—Palmprint, Statistical features, Wavelet, Minimum distance classifier, Majority voting.

I. INTRODUCTION

IDENTIFICATION has always been required in critical tasks and applications; to ask for an object or a signature that only the right person possesses. Throughout history, there were always attempts to make this process flawless and secure, mostly to prevent forgeries. For centuries, identity was confirmed through an item or a mark. Today, there are many ways for a person to identify himself or herself, including passwords, keys and something that is very difficult to duplicate quickly; features of the person himself, also known as biometric data. The latter began in the late 19th century with the collection of fingerprints for forensic purposes due to them being unique to every person from whom they are sampled. Afterwards many other characteristics were deemed efficient and unique to be used in the areas of security and identification. Various algorithms have been used on an individual’s biometric data such as fingerprints [1], iris patterns [2], face [3] and palmprints [4]. Sometimes even several methods are used together and then cross-referenced to dramatically increase the verity of the judgment.

We chose palmprints to be our focus in this work, because we believe that despite their more simplicity than fingerprints which casts the illusion that their use is less secure, they can be utilized just as reliably. Palmprints are more economical in the sense of acquisition. They can be easily obtained using CCD cameras. They also work in different conditions of weather and are typically time-independent. However, due to sampling limitations, lighting and other factors, they may pose problems like insufficient data due to unclear wrinkles or confusion due to poor image quality. This is the reason there are usually many different samples from every person in the database.

The primary characteristics of a palmprint are the principal lines and wrinkles running through it. There are three principal lines in palmprints which are usually called heart line, head line and life line. Their depths, pattern and angles are unique for every person. There are also geometrical features for the palm itself.

Like all biometric data, the key is to use image processing and machine learning approaches to extract distinct traits of every person, called features, by their samples and use the captured data for the next data to come. Being a popular area of research, there are many set of features and different approaches used for palmprint recognition [4]: however, two general approaches for palmprint recognition are the following:

1) Transforming palmprints into another domain and extracting the features in the transform domain. Popular transform domains include wavelet, Fourier, Gabor and Karhunen-Loeve transform.

2) Trying to extract principal lines and wrinkles and other geometrical characteristics as discriminants.

There are a lot of transform-based approaches. Li proposed Fourier-based features for palmprint recognition [5]. Jing used DCT-based features in [6]. The features were extracted by an improved Fisherface method for the DCT domain and used nearest neighbor classifier for the recognition task. Pan [7] utilized a set of Gabor-based features for palmprint recognition. Wu [8] presented a wavelet-based approach for palmprint recognition. They used wavelet energy distribution as a discriminant for the recognition process. Connie [9] proposed to use PCA and ICA for palmprint recognition. There are also several line-based approaches. Palm lines are very useful features of palmprints. Chen [10] proposed a recognition algorithm that primarily uses creases. They extract all creases from a palm and use them for palmprint matching. The main advantage of this algorithm is that it is rotation- and translation-invariant. W. Jia [11] used robust line orientation code for palmprint verification. A few groups used image coding methods for palmprint recognition, such as Palm Code, Fusion Code, Competitive Code, Ordinal Code [12]. A survey about palmprint recognition algorithms before 2009 is provided by Kong in [4].

In the more recent works, in [13], Mistani proposed to use the energy of palm images in spatial and frequency domains as
a hybrid feature and they achieved a high accuracy using this algorithm. In [14], Xu proposed a quaternion principal component analysis approach for multispectral palmprint recognition which achieves a high accuracy rate. A new method is also discussed in [15], where Li presents a three-dimensional palmprint recognition system which can calculate the curvature of the palmprint samples and use them in a rather simple and effective way to determine the identities.

In this work, we have used the palmprint database created by the Polytechnic University of Hong Kong (PolyU) [26] which includes a set of 12 palmprint samples from 500 people under four distinct light spectra. The job of the identifier is to take the picture of a new palmprint sample called a test subject and determine the person in possession of the most similar palmprint.

Here we decided to use a set of features which capture the palmprint information both in spatial and frequency domains. We extract 5 statistical features to capture essential spatial information and 9 wavelet-based features to capture the frequency content of the image. Since wavelet is sensitive to small differences between two images, the wavelet-based features can detect the partial differences between different palms.

Our dataset allows us to use multiple spectra of the same palmprint. Multispectral methods require different samples of the same object in order to make a better decision. In this paper, it is assumed that in the image acquisition section, four images of each palm sample are acquired using four CCDs. These images are then preprocessed and the regions of interest (ROI) for each of them are extracted. So no more preprocessing is required before feature extraction. Four different sample palmprint images are shown in Figure 1.

![Four sample palmprints](image)

After feature extraction, we have to use a classification algorithm to identify palmprints. In this work, two different classifiers are used, the first one being minimum distance classifier and the other one is the weighted majority voting algorithm.

We have also taken advantage of the multispectral nature of the available dataset to improve the exactness of our system.

Section II provides a detailed explanation of features and extracting them. The minimum distance classifier and weighted majority voting algorithms are explained in Sections III-A and III-B respectively. Experimental results are given in Section IV. We provided a comprehensive comparison with other state-of-the-art algorithms there. Conclusion is given in Section V.

II. FEATURES

In general, features play a crucial part in the area of machine learning. Usually the more informative features are, the higher accuracy will be. Therefore it is of utmost importance to extract a set of features which have the required information for prediction of the target value. Once the images are dealt with, it is usually needed to extract a set of features from them to use for prediction. Because images by themselves are very high-dimensional data and they contain a lot of redundant information. There are different approaches for feature extraction [17].

There are different kinds of features that can be used for palmprint recognition. One type consists of spatial and statistical features such as intensity value and higher order moments. Another type is transform-domain features such as wavelet-based, Fourier-based and Gabor-based features. Another category is the geometrical features based on principal lines and wrinkles. The other category requires to extract these lines from the palmprint first, which may not be very simple for low-resolution images. Geometrical features can be very useful in various domains of medical image analysis such as chromosome segmentation in which one can use the geometrical characteristics of chromosomes to segment them from other objects [13].

Here a set of features is used to capture the behavior of the palmprint in both spatial and frequency domains. Based on the simulations, this results in a very highly accurate identification method for palmprints. Two images may have similar global characteristics but look different in local regions. Thus the local features are extracted from different parts of each palmprint and combined to create a feature matrix for every image.

Each palmprint is divided into non-overlapping blocks, and from each block, 5 statistical and 9 wavelet-based features are derived which are expected to capture the frequency information of the palms. To obtain the statistical features of each block, it is necessary to find the histogram of pixel intensities first.

Let us assume that \( B(i, j) \) represents the pixel value at the location \((i, j)\) of a block of size \( N \times N \) (here \( N = 16 \)) and that \( p(k) \) denotes the probability mass function for the \( k \)-th pixel value, \( v(k) \), in that block. Now the 5 following attributes can be defined as the statistical features of the current block:

\[
\begin{align*}
    f_1 &= E[v] = \sum_{k=1}^{K} p(k)v(k) \\
    f_2 &= E[(v - E[v])^2] \\
    f_3 &= E[(v - E[v])^3] \\
    f_4 &= E[(v - E[v])^4] \\
    f_5 &= \text{Entropy}(p) = -\sum_{k=1}^{K} p(k) \log_2 p(k)
\end{align*}
\]

where \( K \) denotes the number of different pixel values in the
The other 9 features are wavelet-based (a short introduction to wavelet is presented in Appendix I). In this work, the wavelet transform used is the first-order Daubechies filter [19] which is essentially the same as Haar wavelet. The 2D-wavelet decomposition is performed up to three stages and in the end 10 sub-bands are produced. Since the mean pixel intensity is used as a statistical feature already, it is not efficient to use the LL sub-band of the last stages, but all other 9 sub-bands may be utilized. We extract the wavelet features in our implementation using the following algorithm:

1) Divide each palm image into $N \times N$ non-overlapping blocks;
2) Decompose each block up to 3 levels using Daubechies 2 wavelet transform; and
3) Compute the energy of each subband and put the similar subband energy of all blocks in a vector.

If each sub-band is denoted by $d_8$, where $i = 1, 2, ..., 9$, the wavelet features can be derived as follows:

$$f_6 = E[d_1^T]$$
$$f_7 = E[d_2^T]$$
$$...$$
$$f_{14} = E[d_9^T]$$

Note that $d_1, d_2, d_3$ are blocks of size $\frac{N}{2} \times \frac{N}{2}$, $d_4, d_5, d_6$ are blocks of size $\frac{N}{4} \times \frac{N}{4}$, and $d_7, d_8, d_9$ are blocks of size $\frac{N}{8} \times \frac{N}{8}$. An example of 3-level wavelet decomposition of a palmprint is presented in Figure 2.

Therefore there will be a total number of $14 \times M$ features for each palmprint image.

### III. Recognition Algorithm

The goal of palmprint recognition is to identify a person using their palmprint samples. It is possible to use the derived features of each person for identification. After finding the features of all people in the dataset, a classifier is required so that the features of each test palmprint can be compared with all of the available samples in the dataset and find the most similar one. There are different classifiers that can be used for this job; for example, minimum distance classifier and probabilistic neural networks. In our work, two different classifiers are used. One is the minimum distance classifier which finds the most similar palmprint by minimizing a distance between the features of the test samples and those of the training samples. The other one is the weighted majority voting algorithm which finds the most similar palmprint by acquiring the predictions based on each feature and its weight, each time awarding the training data with points, and choosing the entry with the highest point. These two algorithms are described in the following sections. Since there are enough data in our dataset, our only goal is to minimize the recognition error on test samples, but if one is dealing with a small dataset, he should also care about the over-fitting problem. One such work is presented by Minaee [20] in which he designed an algorithm to maximize both prediction accuracy and model reliability.

#### A. Minimum Distance Classifier

The minimum distance classification is a popular algorithm in the template matching area. Basically, it finds the distance between the features of an unknown sample and those of the training samples and picks the training sample which has the minimum distance to the unknown as the predicted label. Therefore if $F^{(t)}$ denotes the features of a test sample and $F^{k}$ denotes the features of the $k$-th sample in our dataset, minimum distance assigns the test sample to one of the samples in the dataset such that:

$$k^* = \arg\min_k \| \text{dis}(F^{(t)}, F^{k}) \|$$

Here, Euclidean distance is used which results in the nearest neighbor classifier.

In this algorithm, the feature matrix of all palmprints are extracted first. Considering size of the image and the block, each feature matrix has a size of $14 \times 64$.

As previously mentioned, there are 500 different persons in the database, and for each, there are 12 sample images. Every time, $M$ of these 12 samples are assigned as training and the remaining ones ($12 - M$) as test samples, leading to a total of $500(12 - M)$ test samples. For each person, the feature matrix is defined as the average of the feature matrices of the $M$ different training images of that person. Then, for an unknown sample with the feature matrix $F^{(t)}$, the following
of the feature in that stage. This reward is also applied to a
with any subject is awarded points based on the coefficient
from the training period is calculated. The minimum distance
the feature vector of every sample and the average matrix
subjects and, for every existing spectrum, the distance between
training data are gathered and the feature average for every
random set of the 12 images. Then, the features of the all the
database so that the training part can use different data from a
field. First, the images of every single person are shuffled in

score will decide to which profile the test image is the most
which points will be awarded to each person. When added, the
final verdict is given. Here the voters are the features and the
voting, every voter decides the outcome of the test on its

B. Weighted Majority Voting

Voting theory has many applications in AI, search engines and
recommendation systems. In algorithms based on majority
voting, every voter decides the outcome of the test on its
own and in the end, all the decisions are counted and the
final verdict is given. Here the voters are the features and the
votes are given to every person in the training samples. In
the unweighted case, all features have the same impact on the
votes and none of them is superior. In the weighted case, which
is used here, each feature has a weight of its own, based on
which points will be awarded to each person. When added, the
score will decide to which profile the test image is the most
analogous.

This scheme has a very simple algorithm and can be
performed in a very short time compared to other works in this
field. First, the images of every single person are shuffled in the
database so that the training part can use different data from a
random set of the 12 images. Then, the features of the all the
training data are gathered and the feature average for every
person is computed. Next, the other images are used as test
subjects and, for every existing spectrum, the distance between
the feature vector of every sample and the average matrix
from the training period is calculated. The minimum distance
with any subject is awarded points based on the coefficient
of the feature in that stage. This reward is also applied to a
matrix shared by all four spectra which holds the total score. In
the end, the person gaining the maximum of the global score
matrix is identified as the answer to the recognition query.

For every feature vector $f_i$, the voting result will be:

$$k^*(i) = \arg\min_k \|f_i^{(t)} - F_k\|_2$$

When $f_i$ finds the person with minimum distance to the test
subject, that person receives a point equal to the weight of the
feature.

If the score of person $j$ based on $f_i$ is denoted by $w_iS_j(i)$
or $w_iI(j = \arg\min_k |f_i^{(t)} - F_k^i|)$, where $w_i$ is the weight of
the corresponding feature and $I(x)$ is the indicator function, the
total score of the $j$-th training sample based on all the features
in the scope of all the colors will be:

$$S_j = \sum_{All\ colors} \sum_{i=1}^{imax} w_iI(j = \arg\min_k |f_i^{(t)} - F_k^i|)$$

In the end, the identification factor $j^*$ will be calculated:

$$j^* = \arg\max_j \left[ \sum_{All\ colors} \sum_{i} w_iS_j(i) \right]$$

IV. RESULTS

We have tested our algorithm on the PolyU multispectral
palprint database \[26\] containing 6000 palmprints captured
from 500 different palms. Every palm is sampled 12 times in
two sessions. Each palmprint contains 4 palm images collected
at the same scene under 4 different illuminations, including
red, green, blue and NIR (near-infrared). Therefore, the total
number of images is 24000. The resolution of each image is
128 × 128. As mentioned before, we are working on ROI
images which are preprocessed palmprint images. Therefore,
no action to align or resize the palm-images is required.

We have studied the palmprint recognition task under sev-
eral scenarios. First of all, in each scenario, we have performed
palprint recognition for different fractions of training and
test images. Correct identification takes place when the test
palprint is classified for an entry whose
tag is different from that of the correct palmprint. We have
performed each experiment for two different sets of features;
one using statistical features only (the first 5 features); and the
other using both statistical and wavelet features (total of 14).

For the majority voting algorithm, results with and without
applying the weights were almost the same and therefore only
one is reported. The results of this algorithm are presented in
Table III. Every result is produced by repeating the experiment
10 times and taking the average of their results in order to
make it more precise.

Experiments were also conducted for the minimum distance
classifier, results for different scenarios are presented in Table
III. The effects of different feature sets and also feature
importance weight in the cost function can be seen.

Table III shows a comparison of the results of our work
and those of two other highly accurate schemes. We have
compared our work with methods which were introduced in
recent years. The results are reported for different number of
training samples and blank spaces under QPCA are because in their work, the accuracy was reported only for 6 training samples. As it can be seen, the algorithm utilized in this paper outperforms the other two methods.

### TABLE III
**Comparison with other algorithms for palmprint recognition**

| Training sample fraction | QPCA [14]  | Hybrid feature [13]  | Proposed method (MDC) | Proposed method (WMV) |
|--------------------------|------------|----------------------|------------------------|------------------------|
| 6/12                     | 98.13%     | 98.88%               | 98.45%                 | 98.77%                 |
| 5/12                     | -          | 98.45%               | 98.08%                 | 99.65%                 | 99.99% |
| 4/12                     | -          | 98.45%               | 98.08%                 | 99.65%                 | 99.99% |

The system is implemented using MATLAB on a laptop with Windows 7 and Core i7 CPU running at 2GHz. The execution time for the proposed method is about 0.05s and 0.28s per test using majority voting algorithm and minimum distance classifier respectively. These values are fast enough for real-time application.

### V. Conclusion

This paper proposed a set of statistical and wavelet-based features for palmprint recognition. One attempts to capture the spatial information of palm images and the other aims to mostly capture the frequency content of palm images. One of them is sensitive to the major difference between different palms, while the other is more perceptive of the partial differences between similar palmprints. Two different classifiers are used to perform the recognition process. By using this method, our algorithm is able to identify palmprints with similar line patterns as well as unclear palmprints. The proposed algorithm has significant advantages over the previous popular methods.

The used features 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 3. In the future, we will apply this set of features to other biometrics as well.

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### APPENDIX I. DISCRETE WAVELET TRANSFORM

The Discrete Wavelet Transform (DWT) is a powerful computational tool for a variety of signal processing applications such as image compression [21] and image denoising [22]. Perhaps one of the most famous examples of wavelet is in the JPEG2000 [23], a popular image compression standard. One of the key advantages of wavelet over Fourier transforms is temporal resolution, which means wavelet can capture both frequency and spatial information.

The first literature which was related to the wavelet transform is Haar wavelet which was proposed by the mathematician Alfred Haar in 1909. In 1981, geophysicist Jean Morlet and the physicist Alex Grossman invented the term “wavelet”. In 1988, Mallat proposed the concept of multiresolution [24] which was a key step in the development of wavelet. As the name implies, multiresolution theory is concerned with the representation and analysis of signals in more than one resolution, based on the idea that some features may go undetected in one resolution while they may be easily spotted in another. In the same year, Ingrid Daubechies devised a systematic way to construct the compact support orthogonal wavelet [25]. Daubechies wavelets are the most commonly used set of discrete wavelet transforms in today’s applications.

Here we will explain Haar wavelet, the most basic wavelet transform. Haar transform decomposes a signal into two components at each step, one being the average of pairs of signal values and the other being their differences. If we denote the original signal by \( x(n) \), then the decomposition into two components, \( a(n) \) and \( b(n) \) will be:

\[
\begin{align*}
a(n) &= \frac{1}{2} \left[ x(2n) + x(2n + 1) \right] \\
b(n) &= \frac{1}{2} \left[ x(2n) - x(2n + 1) \right]
\end{align*}
\]

Here \( a(n) \) captures the low frequency components of the signal and \( b(n) \) captures the high frequency component. As it can be seen from the above equations, if the original signal is constant, the high frequency component, \( b(n) \), will be identically zero. This decomposition can be represented with a block diagram as shown in Figure 3.
By having \( a(n) \) and \( b(n) \) we can easily reverse the decomposition to recover the original signal as:

\[
\begin{align*}
  x(2n) &= a(n) + b(n) \\
  x(2n + 1) &= a(n) - b(n)
\end{align*}
\]

If we repeat the AVE/DIFF signal decomposition procedure a number of times, each time, on the average signal \( a(n) \), we will get the Haar transform. As an example, the decomposition up to three stages is shown in Figure 4:

All other one-dimensional DWT can be viewed as a pair of FIR filters, a low-pass filter and a high-pass filter, each followed by a downsampler as depicted in Figure 5.

To implement the low-pass and high-pass filters of Daubechies 4 wavelet, the following difference equations should be used:

\[
\begin{align*}
  a(n) &= a_0 x(2n) + a_1 x(2n + 1) + a_2 x(2n + 2) + a_3 x(2n + 3) \\
  b(n) &= a_3 x(2n) - a_2 x(2n + 1) + a_1 x(2n + 2) - a_0 x(2n + 3)
\end{align*}
\]

where:

\[
\begin{align*}
  a_0 &= \frac{1 + \sqrt{3}}{4\sqrt{2}}, a_1 = \frac{3 + \sqrt{3}}{4\sqrt{2}}, a_2 = \frac{3 - \sqrt{3}}{4\sqrt{2}}, a_3 = \frac{1 - \sqrt{3}}{4\sqrt{2}}
\end{align*}
\]

Using Daubechies 4 wavelets for linear signals, the high frequency component of decomposition, \( b(n) \), will be identically zero and the low frequency component will be a linear signal. Therefore the wavelet representation will be entirely zero for \( b(n) \) of all stages. Daubechies designed a method to construct new decompositions with this property for polynomials of any order. Therefore Daubechies filters result in a sparse representation of polynomial signals. The sparsity of wavelet coefficients is in fact what makes wavelet transform so popular, because this sparsity can be used for signal compression and also signal denoising.

### A. Two-dimensional wavelet transform

To apply wavelet transform to images and other two-dimensional signals, we need to have a two-dimensional version of wavelet. This can be accomplished in one of the two ways; either by applying the 1D wavelet filters first along the rows of the data, and then applying them along the columns of the previous results as depicted in Figure 6; or by applying four matrix convolutions, one for each low-pass/high-pass, horizontal/vertical combination.

Therefore after each stage of 2D wavelet transform on an \( N \times N \) image, we will have 4 images of size \( \frac{N}{2} \times \frac{N}{2} \). An example of 2D wavelet transform which is applied to the standard cameraman image is denoted in Figure 7.

As it can be seen, the upper-left wavelet subband (LL component) contains the low-pass component of the image and other subbands (LH, HL and HH) contain horizontal, vertical and diagonal edges and structures of image respectively. Wavelet-based feature extraction has a lot of applications in different areas, such as image processing, EEG signals and phoneme recognition.

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