Biometric Identification Using a New Direction in Contactless Palmprint Imaging

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Abstract— For the purpose of biometric applications, we explore in this paper a new approach to characterize palmprint features. In recent years, the contactless system emerges as a new viable option to address hygienic issues and improve the user acceptance. In this paper, we examine the issues related to the contactless imaging and we propose a new approach for palmprint recognition captured in contact free settings and without constraint on the capture environment. For the step of hand detection, our approach is based on a data-mining process for skin color modeling. To improve the achieved results and to determine the hand region in the image, a succession of post-processing was proposed. For the step of palmprint recognition, our approach is based on a new global approach that focuses only on areas of the image having the most discriminative features for recognition. The presented approach was evaluated experimentally on a real contactless palmprint database, namely, “Sfax-Miracl hand database”; the results of this evaluation show promising results and demonstrate the effectiveness of the proposed approach.

Keywords: Contactless palmprint recognition, Skin color model, Data-mining, Local binary patterns (LBP), Sequential forward floating selection (SFFS).

1. Introduction

Automatic personal identification is becoming an impending and crucial problem that needs to be solved properly. Biometrics, which deals with identification of individuals based on their biological or behavioral characteristics, has been emerging as a new and effective identification technology. Thanks to this technology, confidence in identification results is higher since the person to identify must be physically present. Recently, a novel hand-based biometric feature, palmprint, has attracted an increasing amount of attention. Palmprint based identification system has several advantages such as stable line features, rich texture features, low-resolution imaging, low-cost capturing devices, easy self positioning, user-friendly interface, etc. Due to its advantages, palmprint recognition has attracted increasing attention during recent years for many mission critical applications, such as homeland security, e-commerce, banking, etc.

1.1 Related Works

Although palmprint is relatively a new biometric technology compared to others, e.g. iris and fingerprint, a number of interesting approaches in this field have been proposed in the literature over the last ten years. The proposed palmprint recognition approaches can be classified into mainly two popular categories. The first category groups the structural approaches such as those based on principal lines [1], wrinkles [2], ridges and features point [3] which are considered as useful features for representing palmprints. Unfortunately, the efficiency of the recognition is impeded by the resemblance among principal lines of different individuals and the often poor quality of wrinkles in some palmprint images. Besides, wrinkles and ridges of the palm are always crossing and overlapping each other, which complicates the feature extraction task. The second category of palmprint recognition approaches contains the global approaches; these latter are the most intensively studied and they are used in the field of feature extraction and pattern recognition, e.g. Gabor filters [4], Eigenpalm [5], Fisherpalms [6], Fourier transform [7], Texture energy [8], Various invariant moments [9], Morphology operations [1], [10] and Local Binary Patterns [11], [12], [13]. Given their proven efficiency in various similar application domains, global approaches could also be used efficiently for palmprint recognition. Although extensive research have been conducted in finding effective ways to represent the palmprint features, not much detail of how the palmprint images were acquired was discussed in the literature. In fact, in all these approaches, palmprint images are taken with contact with the capture system, therefore, all the users are obliged to touch the same glass, and some artifacts can be created during the acquisition according to the pressure of users on the plate glass which leads to non hygienic conditions. Besides, latent palmprint which remains on the system’s surface could be copied for illegitimate uses. Recently, few studies [14], [12] are interested in making it more comfortable and more hygienic by removing the requirement of contact. Therefore, there is pressing need for a contactless palmprint biometric technology. Hand detection process from these acquisitions is a complex task. In fact, hand detection suffer from the variation of the background (complex environment, simple environment, etc.), the variation of the position and the
orientation of the hand, the variation of the hand size which vary according to the distance of the hand from the capture system, the variation of the lighting conditions (indoor and outdoor environments), the presence of hand’s accessories (ring, bracelet, watch, etc.), etc.

1.2 Contribution of the Work

In this paper, a new approach is investigated by developing an accurate and robust method for palmprint recognition detected from freely posed hands in contact free settings and without constraint on the capture environment. The main contribution of this work consists of using a data-mining process as a new philosophy of data processing for skin pixels detection. Previous researchers mostly use the entire area of the palmprint as input to their recognition algorithms. Therefore, this approach focuses only on areas of the image having the most discriminating features for recognition. This selection aims at essentially ignoring regions with useless information and hence reducing the complexity of the recognition algorithm in terms of both space and time.

The remainder of this paper is organized as follows: Section 2 describes the proposed process of hand recognition. Sections 3 and 4 present the experimental results to show the effectiveness of the proposed approach and draw conclusions on our work, respectively.

2. The Proposed Recognition System

The pipeline of our proposed biometric recognition system consists of four steps: (1) preprocessing, (2) feature extraction, (3) sub-region selection, and finally, (4) matching and decision making.

2.1 Preprocessing

The palmprint preprocessing step is used to robustly locate the Region Of Interest (ROI) of the palm. We can distinguish in this step two essential phases. First, we start with a detection phase of the hand region, followed by a ROI extraction phase. The details of the preprocessing step are provided in the following sections.

a) The Proposed Process of Hand Detection Method

In biometric recognition systems, a precise and fast hand detection process must be elaborated. In this section, we briefly describe our hand detection method which is composed of two steps: (1) data-mining process to construct the adequate prediction model to skin pixel detection and (2) post-processing step to refine the hand detection results and to only conserve the hand region.

i) Data-mining: Skin Color Modeling

The proposed prediction model is developed from a supervised learning on a set of labeled pixels. These later are extracted automatically from the training images and their corresponding binary masks (Fig. 1.) using “Sfax-Miracl hand database” of skin color and non skin color images. In our work, we computed for each pixel its representation in various standard color spaces such as: RGB, HSV, YCrCb, normalized RGB. This leads to a features vector composed of 12 variables. With each pixel features vector is associated its class label denoted as 1 for skin color and 0 for non skin color. An extract of the training data set file is illustrated in Fig. 1.

![Fig. 1: An extract of our training data set file.](image)

The images are often represented in RGB space. Depending on the application, the image features are more perceptible in some color space than others. Therefore, the choice of the color space is very important for representing the image. In our work, we study different color spaces and we try to find the most discriminative set of color axes among them. Therefore, we need a variable selection step to determine the color space where the skin detection performance is the best. Such a space can be a standard color spaces or a new kind of hybrid space by selecting a set of color axes from different standard color spaces. To achieve this selection, we used the Relief algorithm [15] as a variable selection method. To reduce the complexity of the study, we were limited to the use of three axes for the characterization of skin color which represent the 3 best variables. We discover that the three color axes H, S and Cr is the most discriminative for skin detection which constitute a new hybrid color space HScr. After that, we were interested in building a predictive model to identify whether a pixel is a skin pixel or not from the various descriptors. Many classification techniques from the statistics and machine learning communities have been proposed [16], [17], [18], [19], [20]. A well-accepted method of classification is the induction of decision trees [21], [16], [19], [20]. Therefore, in our work we used the techniques based on the graphs of decision tree which allow an automatic choice of the decision rule. A decision tree is a flow-chart-like structure consisting of internal nodes, leaf nodes, and branches. Each internal node represents a decision, or test, on a data attribute, and each outgoing branch corresponds to a possible outcome of the test. Each leaf node represents a class. In order to classify an unlabeled data sample, the classifier tests the attribute values of the sample against the decision tree. A path is traced from the root to a leaf node which holds the class prediction for that sample. Improved C4.5 [22] is a widely used technique for data-
mining. As a result of applying this technique to a training set, a graph of decision tree is built as illustrated in Fig. 2.

From the obtained graphs of decision tree, each path corresponds to a rule expressed as “IF condition THEN conclusion” in which “condition” denotes a disjunction of conjunctions of logical propositions of type “attribute value”. The set of obtained rules represent our prediction model.

ii) Post-processing Step

The result of detection produced by the previous step may contain hand regions that are corrupted by false detection. Therefore, this step performs a succession of post-processing for the result of previous detection (Fig. 3(b)) to resolve this false detection. We started by applying morphological operators: a dilation and opening with a circular structuring element. The first morphology operation: dilation with a circular structuring element of radius 1 to group neighboring pixels in order to fill any small hole in the hand area and to eliminate some fragmented regions without picking up the fragmented fingers between them. Then, the second morphology operation: the closing to remove any small objects in the background area in order to preserve only the larger white objects in the image e.g. hand. The result of morphology operations is shown in Fig. 3 (c).

As our solution to hand detection will be used for biometric recognition application, one hand is supposed to be present in the system. Thus, the region with the largest area is preserved and considered as a hand. The regions with an important area and elongation are conserved as well (Fig. 4(b)). There may be fingers disconnected from the hand for users wearing rings. To resolve this problem, we apply a closing morphology operation with a linear structuring element oriented along the finger ellipse. The result of closing morphology operation is shown in Fig. 4(c).

Fig. 4: Hand region determination: (a) skin detection results (b) hand image after conserving the region having the largest area and the regions with important area and elongation (c) hand image after closing morphology operation application.

b) Region of Interest (ROI) Extraction

To extract the ROI of the palmprint image, our system is based on the detection of the four local minima (Finger-webs) which are focused on the hand contour. Once these points are detected, it is possible to classify the hand into left hand or right hand. This classification serves us to locate the ROI.

i) Finger-webs Determination

Localizing hand extremities like finger-webs between fingers is the first and the most important step in ROI extraction. The precision and robustness requirements on this step are high otherwise recognition will suffer from measurement errors. In order to detect the four finger-webs, we apply the radial distance to a reference point technique [23]. First, the middle point Wm of where the arm or wrist region crosses the image edge is chosen as the reference point [23] as shown in Fig. 5 (a) and an Euclidean distance to all the border pixels from Wm is calculated. Then, a distance distribution diagram is plotted (Fig. 5(b)). Finally, we search for the four local minima in this diagram and we mark them as black circles (Fig. 5(b)). The four local minima correspond to the finger-webs in the hand. After determining them from the distance distribution diagram plot, we can find their position in the hand contour pixels. These positions allows us to determine their coordinates in the image (marked as black circles in the hand image as shown in Fig. 5(c)).

This method is affected by height contour irregularities which lead to false peaks detection. So, we use the smoothing method by applying a low pass filter.

ii) Classification of Hands into Right and Left Hand

After determining the finger-webs of the hand, we can determine which side of the hand is used. In fact, our proposed system offers the flexibility for the user to use
one of the two hands for the recognition. Therefore, to
speed up the recognition process, the left and right palms
are stored separately in the database. This step aims to
reduce the number of comparisons and subsequently reduces
computation time and recognition since only half of the
database needs to be searched by knowing which side of the
hand is used. This reduction is very interesting for real-time
applications. The following rules are applied to determine
the right and left hands:

- If \( Y_1 > Y_4 \) then left hand
- If \( Y_1 < Y_4 \) then right hand

Where \( Y_1 \) and \( Y_4 \) are vertical positions of the first and fourth
local minimum ordinates previously detected.

### iii) Region of Interest (ROI) Location

For palmprint analysis, a region of interest (ROI) of the hand
is first extracted. This latter must be extracted independently
of the distance between the hand and the capture system.
Our extraction is based on hand dimensions and the palm
extraction method described by Doublet et al. [14] which
is inspired from the method proposed by Zhang et al.[4].
In the work of [14], the width of the palm is calculated by
the Euclidean distance between two points which represents
two landmarks points in the hand shape obtained after
applying an active shape model. These landmarks are defined
using hand shape characteristics. After conducting initial
experiments, the two landmarks points proposed by Doublet
et al. [14] are fixed at the 30th and 125th landmark points. In
our work, these two points are defined differently depending
on the hand size. To determine the width of the palm, a line
is formed between points A and B which correspond to the
second and fourth local minimum detected earlier if the hand
is a left hand, otherwise they are the first and third local
minimum if the hand is a right hand (Fig. 6 (a) and (b)).
Then, we trace the mediator OE of the segment \([AB]\) with
\([OE] = 1 / 2 \ [AB]\). Finally, we trace the segment that passes
through the point E, which is perpendicular to the segment
\([OE]\), its intersection with the edge of the hand corresponds
to the two points F1 and F2. The Euclidean distance between
the point F1 and F2 gives us the width of the palm denoted
L. Fig. 6 (a) and (b) shows the determination of the width
of the palm. Once the palm width L is determined, we
create the ROI based on the palm dimension. According to
the literature, the ROI used for the palmprint recognition is
defined as the central part of the palm in a square shape.
Thus, we begin first by tracing the segment \([OO_1]\), which is
perpendicular to the segment \([AB]\) with \([OO_1] = 1 / 10 \ L\)
[14], then we trace the segment \([E1E2]\) that passes through
the point O1 and perpendicular to the segment \([OO_1]\) with
\([E1E2] = 2 / 3 \ L\) [14], finally we continue to trace the other
three sides: [E1E3], [E3E4] and [E4E2], each having the
same size \(2 / 3 \ L\). Fig. 6 (c) shows the creation of the ROI.

Fig. 6: Region of interest location (a) and (b) palm width L
determination (c) ROI creation with \([OO_1] = 1 / 10 \ L\) and
\([E1E2] = 2 / 3 \ L\).

After locating the ROI, we apply a mask having the same
size and shape on the original image in order to extract the
ROI from the rest of the hand.

As the ROI may have different sizes and orientations, a
normalization step is necessary. First, the images are rotated
to the right-angle position by using the vertical axis as the
rotation-reference axis. Finally, as the size of the ROI varies
from hand to hand, they are resized to a standard image size.
In our work, the images are resized to \(T^*T\) with \(T = 180\)
pixels.

### 2.2 Feature Extraction

From preprocessing, the palm features must be extracted.
Local Binary Patterns (LBP) operator, being introduced by
Ojala et al. in 1996 [24], is an effective feature extraction
method in pattern recognition. Its high discrimination ability
and simplicity in computation have made it very suitable for
online recognition system. This operator is, by definition,
invariant against any monotonic transformation of the grey
scale. Moreover, it can discriminate a large range of rotated
textures efficiently. Due to these advantages, LBP is able
to deal with all possible variations including pose variation,
luminance variation, and light noise of palmprint images.
The LBP operator labels every pixel by thresholding \(n \times n\)
neighborhoods with the center value. The result is recorded
as a binary number and the histogram of the labels is
considered as a texture descriptor. To improve the robustness
and generalization ability of the original LBP operator, it has
been extended by Ojala et al. in 2002 [25] to take account
neighborhoods of different sizes and shapes using bilinear
interpolation. Therefore, the multiresolution analysis can be achieved by choosing different values of $P$ and $R$, where $P$ denotes the number of neighboring pixels with respect to the center pixel, and $R$ represents the distance from the center pixel to each of the neighboring pixels.

Another extension in [25] to the basic LBP operator is the so-called uniform LBP that is found to be the fundamental property of local image texture. The LBP is called uniform if there are no more than two 0/1 or 1/0 bitwise transitions in its binary code. The authors in [25] also found that only 58 of 256 LBP patterns are uniform. The authors in [26] found in their experiments with texture images, that 90% of patterns are uniform. That is to say, the uniform patterns take a majority percentage of all patterns. As a result, each uniform pattern is given a unique label in histogram calculation. Subsequently, the amount of data can be reduced significantly by constructing a histogram of dimension 59. The 58 first bins will contain the occurrences number of each uniform patterns, the last will contain the occurrences number of all not uniform patterns. This combination reduces the size without losing much useful information. In this paper, in order to describe the palmprint image, all the LBP feature value is quantified into [1; 59] by using the uniform criterion. The whole procedure of our palmprint feature extraction is illustrated in Fig. 7.

![Fig. 7: Diagram of palmprint feature extraction.](image)

2.3 Discriminative Sub-region Selection

The objective of this step is to select the sub-regions having the most discriminating features for recognition instead of using the whole image as input for the recognition algorithm. For this, we need a feature selection method. Several possible feature selection methods have been proposed in the literature. With its good accuracy, we used the SFFS, developed by Pudil et al. in 1994 [27], as a feature selection method in our work.

SFFS is the top-down searches that successively delete features from a set of original candidate features in order to find a smaller optimal set of features. The principle of the SFFS algorithm is as follows: it allows adding features at each step and deletes multiple as the subset result improves the objective function. So we use the previously extracted features (e.g. Histograms) of each sub-region for classification by the SFFS algorithm and we select the classifiers that represent the most discriminating sub-regions for the recognition of the palmprint based on the objective function: the minimization of the false classification rate. The objective function $E$ that we used to select the most discriminating sub-regions is to minimize the false classification rate and is calculated as:

$$E = \frac{\text{Number of false classified images}}{\text{Total number of images}}. \quad (1)$$

This objective function is obtained by summing up all the false classification rates generated for each classifier selected by the SFFS algorithm. For example, the false classification rate $E_{S_n}$ of the pool of classifiers selected by the SFFS algorithm, given by $S_n = \{C3 \ C6 \ C9\}$, is obtained as follows:

$$E_{S_n} = E(C3) + E(C6) + E(C9). \quad (2)$$

2.4 Matching and Decision Making

Once the features vector is obtained, we need to compare the input image with the training images in the database to determine which training image is most similar to the input image that represents the identity of a user. To show the matching performance of the proposed approach, we have used the following chi-square ($X^2$) statistic:

$$X^2(H^P, H^G) = \sum_{i=0}^{l} \frac{(H^P_i - H^G_i)^2}{(H^P_i + H^G_i)}. \quad (3)$$

where $l$ is the length of the features vector of the palmprint image, $H^P$ refers to a target palmprint histogram and $H^G$ to a model palmprint histogram. Note that the choice of the $X^2$ measure is motivated by the experimental findings seen in [26] which shows that $X^2$ gives better results than other dissimilarity measures such as the histogram intersection $D(S, M)$ and Log-likelihood statistic $L(S, M)$.

3. Experimental Results and Evaluation

To evaluate the performance of the proposed approach, a real contactless palmprint database named “Sfax-Miracle hand database” has been built. This database contains 1080 images collected from 54 individuals acquired in uncontrolled conditions in a single session. By uncontrolled
conditions we mean a database acquired in operative conditions with background and illumination unsupervised. “Sfax-Miracl hand database” is constituted from images captured from the left and right hands. Considering each hand as an independent user, we have 108 different hands images with a number of 10 images per user. These images were acquired by a digital camera having a resolution of 1024 * 768 pixels and located at a distance between 30 and 50 cm from the palm. The main objective in building this database is to have the unsupervised conditions for the imaging which attempts to represent more realistic application environment. Some examples of acquired images can be seen in Fig. 8.

![Fig. 8: Acquisition of typical images from “Sfax-Miracl hand database”](image)

In addition, our database has the advantage to contain masks in which the skin regions were preserved and the background was replaced by black color. These masks serve us to construct and to validate the performance of the prediction model for skin pixel detection.

In the herein reported experiments, we discuss the results of the matching step such as recognition performance, memory requirement and computation time. In these experiments, a PC with Intel (R) Dual Core Centrino (TM) 1.6 GHz and 1GB random access memory was used.

In order to evaluate the effectiveness and robustness of our approach regarding the selection of the most discriminating sub-regions for recognition, we conduct a comparison between the obtained results with and without the selection of discriminating sub-regions. This comparison is concerned not only the obtained recognition rate but also the size of the features vector and the identification time. For this experiment, we used 10 hand images of the left and right hand captured from 50 users taking from our database and we randomly select 6 images of each hand for the gallery and 4 images of each hand for the probe. The results of this comparative study are presented in Table 1.

Table 1: Comparison of the recognition rate, the size of the features vector and the identification time without and with selection of discriminating regions.

<table>
<thead>
<tr>
<th></th>
<th>Without Selection</th>
<th>With Selection</th>
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<tbody>
<tr>
<td>Recognition rate</td>
<td>98.66%</td>
<td>98.66%</td>
</tr>
<tr>
<td>Size of the features vector</td>
<td>2891</td>
<td>1416 for left hand</td>
</tr>
<tr>
<td>Identification Time</td>
<td>0.15s</td>
<td>0.07s</td>
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Apart from the promising results in terms of the recognition rate, our method has another important advantage which is its improvement of the required storage space and run-time: a great gain in the size of the features vector which reduces the memory requirements; in addition, the computation time is cut by about two folds which is very interesting for real-time applications of palmprint recognition.

To further evaluate the performance and to demonstrate the novelty of our approach with other works in the area, another comparison has been finally achieved among our work and the work of Polli and al. on 2011[13] using the same conditions as the last experiment. Table 2 compares the experimental results obtained for the one-to-100 matching of our approach with that of Polli and al.

Table 2: Comparison of the obtained recognition rate, the size of the features vector and the identification time from the proposed approach and the work of Polli and al.

<table>
<thead>
<tr>
<th></th>
<th>Our approach</th>
<th>[Polli and al., 2011]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recognition rate</td>
<td>98.66%</td>
<td>98.66%</td>
</tr>
<tr>
<td>Size of the features vector</td>
<td>1416 for left hand</td>
<td>2304</td>
</tr>
<tr>
<td>Identification Time</td>
<td>0.07s</td>
<td>0.085s</td>
</tr>
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According to these experimental results, one first contribution of our approach resides in terms of storage space generated by the gain of more than half of the features vector size. A second contribution is in terms of speed: a decrease in identification time of 0.015 seconds which is very interesting for real-time applications. The showing results confirm the effective of our approach compared to other works published in the area.

4. Conclusions and Future Works

This paper presents a new approach for contactless palmprint recognition. At the first stage, our approach relies on an innovative method for hand detection captured without contact and without constraints on the capture environment which exploit the color information. First, our approach proceeds by selecting a set of color axes from different standard color spaces in order to determine the color space where the skin detection performance is the best. As a result, a new hybrid color space composed of the axes H,
S, and Cr was determined. After that, based on a supervised learning, we determine our prediction model to discriminate the pixels of skin from those of non-skin. Finally, to improve the achieved results and to determine the hand region in the image, a succession of post-processing was proposed. At the second stage, our approach focuses only on areas of the image having the most discriminating features for the recognition. To achieve that, we proceed by partitioning the whole palmprint image into sub-regions and applying the LBP operator within each sub-region. In order to both improve the recognition time and reduce the required memory space, we incorporate a selection step that keeps only the most discriminating regions for recognition. For this selection step, we used the SFFS algorithm.

Experimental results on a real contactless palmprint database “Sfax-Miracl hand database” show that our method can achieve a height recognition rate of 98.66%. In addition to the promising obtained recognition rate, our approach show a considerable decrease in the size of the features vector and the recognition time with the selection of discriminating sub-regions which proves the interest of our approach and also validates our choices.

Our further research efforts are focused to improve our approach by merging each palmprint signature with other useful information such as fingerprint, fingerprint surface, hand geometry, etc.

References