PALMPRINT RECOGNITION BASED ON REGIONS SELECTION

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Abstract: Palmprint recognition, as a reliable personal identity method, has been received increasing attention and become an area of intense research during recent years. In this paper, we propose a generic biometric system that can be adopted with or without contact depending of the capture system to ensure public security based on identification with palmprint. This system is based on a new global approach which is to focus only on areas of the image having the most discriminating features for recognition. Experimental results have been undertaken on two large databases, namely,"CASIA-Palmprint" and "PolyU-Palmprint" show promising result and demonstrate the effectiveness of the proposed approach.

1 INTRODUCTION

The progress in informatics field, the development of common operations as well as the recent threats territories have naturally led the subject of security for a reliable identification of persons. Recently, biometrics has been emerging as a new and effective identification technology. In the biometrics family, palmprint is new but promising member. Palmprint characteristics are relatively stable, unique and the hand present high user acceptability. Usually, palmprint biometrics require contact with the capture system, therefore, all the users are obliged to touch the same glass. For this reason some users refuse to put their hand on the same plate for hygienic reasons. Recently, few studies (Doublet et al., 2007) (Goh et al., 2008) are interested in making it more comfortable and more hygienic by removing the requirement of contact. Although palmprint is relatively a new biometric technology, a number of interesting approaches in this field have been proposed in the literature over ten years ago. There are mainly two categories of approaches to palmprint recognition. The first category is the structural approaches such as based on the principal lines (Wu et al., 2004), wrinkles (Chen et al., 2001), ridges and features point (Duta et al., 2002). Unfortunately, it is difficult to get a good recognition rate while using only the principal lines because of their resemblance among different individuals. Besides, wrinkles and ridges of the palm are always crossing and overlapping each other, which complicates the features extraction task. The second category is the global approaches, such as Gabor filters (Zhang et al., 2003), Eigenpalm (Lu et al., 2003), Fisherpalms (Wu et al., 2003), Fourier transform (Li et al., 2002), Various invariant moments (Kan and Srinath, 2002), Morphology operation (Wu et al., 2004) (Han et al., 2003) and Local Binary Pattern (Wang et al., 2006). The global approach is proved to be the most efficient in the literature, therefore, it could be used efficiently for palmprint recognition. Previous researchers mostly use the entire area of the palmprint as input to the recognition algorithm. The main contribution of this work is to focus only on areas of the image having the most discriminating features for recognition to propose a biometric system for contactless applications.

The remainder of this paper is organized as follows: Section 2 describes the proposed palmprint recognition system. Section 3 presents some experiments and results to show the effectiveness of the proposed approach. Finally, Section 4 summarizes the main results and offers concluding remarks.

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2 THE PROPOSED SYSTEM

The proposed biometric recognition system is composed of four steps: (1) preprocessing (2) features extraction (3) features selection and finally (4) matching and decision making.

2.1 Preprocessing

The goal of preprocessing is to robustly locate the Region Of Interest (ROI) of palm. In our case, the preprocessing step consist of three phases. First, we start with a detection phase of hand image, followed by a ROI extraction phase and finally a ROI preprocessing phase.

2.1.1 Hand Detection

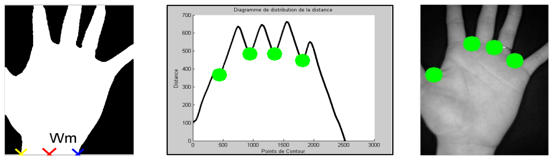
First of all, the palmprint image is rotated 90° in clockwise direction. Next, the image is segmented into foreground and background using the Otsu's method (Otsu, 1979). They can be some fingers disconnected from the hand for the users wearing some rings. Thus, we use morphology operations to resolve this problem and to fill any holes which might eventually be present in the foreground and background of the segmented image. Finally, the binary images are drawn to obtain the contours of hand shape by making use of the border tracing algorithm (Shapiro and Stockman, 2001).

2.1.2 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 would be possible to classify the hand in left hand or right hand. This classification serves us to locate the ROI.

A. Finger-webs Determination
In order to detect the four local minima, we apply the radial distance to a reference point technique (Konukoglu et al., 2006). First, the middle point Wm of where the arm or wrist region crosses the image edge is chosen as the reference point (Konukoglu et al., 2006) as shown in Figure 1.(a) and an Euclidean distance to all the border pixels from Wm is calculated. Then, a distance distribution diagram is plotted (Figure 1.(b)). Finally, the local minima in the distance distribution diagram which represent the Finger-webs locations are found (Figure 1.(c)).

This method has however some disadvantages: it is sensitive to contour irregularities which lead to false peaks detection. So, we use the smoothing method by applying a low pass filter.



(a) (b) (c)

Figure 1: Finger-webs determination (a) Reference point Wm (b) Distance distribution diagram of the hand contour points to a reference (c) Finger-webs locations.

B. Classification of Hands into Right and Left Hand
The proposed system provides the flexibility for the user to use one of the two hands for recognition. Therefore, we apply a classification step for the database. This step allows reducing the number of comparisons and subsequently reducing computation time and recognition time as only half of the database needs to be searched. Therefore, it is very interesting for real-time applications. The following rules shown are applied to determine the right and left hands:

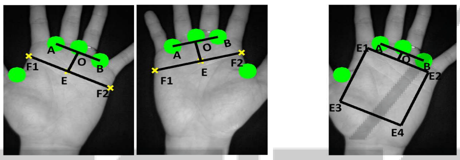
- If $Y1 > Y4$ then left hand
- If $Y1 < Y4$ then right hand

Where Y1 and Y4 are the first and fourth local minimum ordinates previously detected.

This classification rules suffers from a problem in the absence of the thumb which causes the detection of three local minima. To overcome this limitation, we count the number of skin pixels intersected with the left edge, if it exceeds the number of pixels intersected with the right edge so it's a left hand otherwise it is a right hand.

C. Region of Interest (ROI) Location
After hand detection, it is necessary to extract the ROI 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., 2007). In the work of (Doublet et al., 2007), the width of the palm is calculated by the Euclidean distance between two points which represent two indexes in the hand's shape model fixed after experiments at 30 and 125. In our work, these two points are defined differently depending on the size of the hand. To determine the width of the palm, a line is formed between point A and B (Figure 2.(a)). 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 (Figure 2. (a)). Once the palm's width L is determined, we could create the ROI based on palm dimension. We begin first by tracing the segment [OO1], which is perpendicular to the segment [AB] with [OO1] = 1 / 10 L (Doublet et al., 2007), then we trace the segment [E1E2] that passes through the point O1 and perpendicular to the segment [OO1] with [E1E2] = 2 / 3 L (Doublet et al., 2007), finally we continue to trace the other three sides, each having the same size 2 / 3 L. Figure 2. (b) shows the creation of the ROI.



(a) (b)

Figure 2: Region of interest location (a) palm width L determination (b) ROI creation with [OO1] = 1 / 10 L [E1E2]=[E1E3]=[E3E4]=[E4E2] = 2 / 3 L.

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

2.1.3 ROI Preprocessing

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. After that, as the size of the ROI vary 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. Finally, to improve the quality of the image, we attenuate the noise by applying a low pass filter.

2.2 Features Extraction

Features extraction is defined to describe the ROI by the features that best discriminate the palmprint. In our work, we propose a new way to apply the local binary patterns (LBP) texture descriptor.

The LBP operator, being introduced by (Ojala et al., 1996), is a simple yet powerful texture descriptor which has been used in various applications. LBP operator labels every pixel in an image by thresholding its neighboring pixels with the center value. After the labels have been determined, a histogram H of the labels with dimension 255 is constructed as:

$$H_l = \sum_{i,j}\{L(i,j) = l\} \qquad l = 0,\ldots,n-1 \tag{1}$$

Where n is the number of different labels produced by the LBP operator, while i and j refer to the pixel location. To improve the robustness and generalization ability of the original LBP operator, it has been extended by (Ojala et al., 2002) to take account neighborhoods of different sizes and shapes. Another extension to the original LBP operator introduced by (Ojala et al., 2002) is to use so called uniform patterns. Ojala et al also found that only 58 of 256 LBP patterns are uniform. (Ahonen et al., 2004) found in their experiments with texture images, that 90% of patterns are uniform. Subsequently, the amount of data can be reduced by constructing a histogram of dimension 59. The whole procedure of our palmprint features extraction is illustrated in Figure 3.

First, we divided the ROI of the palmprint into r * r non-overlapped square sub-regions R0,..., R (r * r) -1, each of them has the side length of T/r. This division allows us to take into account the spatial relations of the palmprint regions. Then, we apply uniform LBP in the (8, 1) neighborhood within each of the sub-regions to describe the texture features of the palmprint. Finally, the concatenation of histograms produced by each region allows getting a global histogram that represents our features vector.

2.3 Features Selection

When the image has been divided into regions, it can be expected that some of the regions contain more useful information than others in terms of distinguishing between people. Therefore, we use Sequential Forward Floating Selection (SFFS), developed by (Pudil et al., 1994), as a features selection method. The principle of the SFFS algorithm is as follows: it allows adding a features (e.g. sub-region) at each step and deletes multiple as the subset result improves the objective function: the minimization of the false classification rate. The pseudo-code of our features selection algorithm is the following:

Where E_0 is the error rate (false classification rate), Cj refers to the sub-regions, n to the number of selected sub-regions, k to the total number of sub-regions and Sn to the pool of the selected sub-regions.

2.4 Features Matching

Several possible dissimilarity measures have been proposed for histograms. In this work, we use the following X^2 statistic:

$$X^2(H^P, H^G) = \sum_{i=0}^{l} \frac{(H_i^P - H_i^G)^2}{(H_i^P + H_i^G)} \tag{2}$$

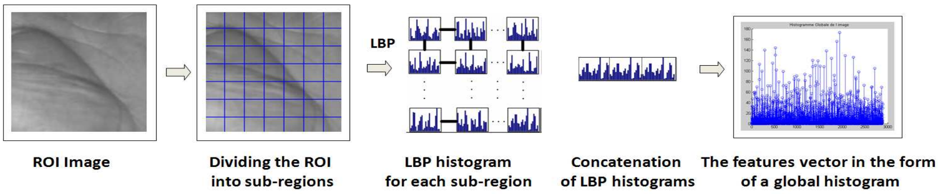


Figure 3: Diagram of palmprint features extraction.

Algorithm 1: Features selection algorithm.

Initialize an empty subset S_0; $E_0 = 100\%$; $n = 0$;
/Find the best feature that minimize the objective function and update S_n $(forward)$/
while $n < k$ **do**
  $C_j = \underset{C_j \notin S_{n-1}}{argmin} \left[E\left(S_{n-1} \cup C_j\right)\right]$
  $S_n = S_{n-1} \cup C_j$
  $E_n = E(S_{n-1} \cup C_j)$
  $n = n+1$
  /Find the worst feature that minimize the objective function and update S_n $(backward)$/
  while $n > 2$ **do**
    $C_j = \underset{C_j \in S_n}{argmin} \left[E\left(S_n \setminus C_j\right)\right]$
    $B_e = S_n \setminus C_j$
    $E_{B_e} = E(B_e)$
    if $E_{B_e} < E_n$ **then**
      $S_{n-1} = B_e$
      $E_{n-1} = E_{B_e}$
      $n = n-1$
    else
      Break
    end if
  end while
end while

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.

3 EXPERIMENTAL RESULTS AND COMPARISON

In this section, we present the experiments performed during the on-line stage. Before presenting them, we will briefly describe the databases used.

3.1 Palmprint Databases

In order to test our recognition process, two palmprint databases are adopted, including "CASIA-Palmprint" Database (CASIA-Palmprint-Database, 2003) and "PolyU-Palmprint" Databases (PolyU-Palmprint-Database, 2005). "CASIA-Palmprint" Database contains 4512 palmprint images captured from 282 subjects. For each subject, we collect 8 palmprint images from both left and right palms. All palmprint images are collected in the same session. "PolyU-Palmprint" Database contains 7752 palmprint images collected of 193 subjects. In this dataset, we collected the palmprint images on two separate sessions. On each session, the subject was asked to provide about 10 images, each of the left palm and the right palm. We used "CASIA-Palmprint" database as a training base for the SFFS algorithm, as well as a basis for evaluating the performance of the whole process of our approach. To validate this performance, we used "PolyU-Palmprint" database.

3.2 On-line Experiments

In our on-line phase, three experiments were conducted for six different divisions using 8 images of each hand of 282 users taken from "CASIA-Palmprint" databases. So, first we randomly selected 5, then 4, and finally 3 images of each hand for the gallery and the rest for the probe. The result of the Recognition Rate (RR) achieved in these experiments is shown in Table 1, Table 2 and Table 3 respectively.

Table 1: Comparison of recognition rates with and without selection using 5 images of each hand for the gallery and 3 images of each hand for the probe.

RR(%)	2*2	3*3	4*4	5*5	6*6	7*7
Without Selection	94,38	95,62	96,67	96,85	96,73	96,98
With Selection	94,38	94,81	96	96,98	96,79	97,53

Table 2: Comparison of recognition rates with and without selection using 4 images of each hand for the gallery and 4 images of each hand for the probe.

RR(%)	2*2	3*3	4*4	5*5	6*6	7*7
Without Selection	92,53	94,46	95,42	95,79	96,20	96,29
With Selection	92,53	94,23	95	96,34	95,46	96,66

These three experiments show a gain in terms of RR for different numbers of divisions into sub-regions and for different numbers of images in the gallery and

Table 3: Comparison of recognition rates with and without selection using 3 images of each hand for the gallery and 5 images of each hand for the probe.

RR(%)	2*2	3*3	4*4	5*5	6*6	7*7
Without Selection	88,93	92,79	93,85	93,92	94,54	94,14
With Selection	88,93	91,52	94	94,14	94,04	94,72

the probe, therefore, the importance of the selection phase. This gain is the result of ignorance of the regions with useless information e.g. regions that increase the intra-class variability among the palmprint images. From the results of the three previous experiments, it is noted that division 7 gives the best identification rate. Therefore, we have opted for division 7 in our work. We also conclude from these three experiments, the effect of increasing the images number in the gallery. According to (Tana and Songcan, 2006), as the number of images per users in the gallery is high, better the performance of the recognition system. Nevertheless, even with a reduced number of images stored in the gallery as shown in the third experiment, the performance of our system is not too affected which proves their robustness and persistence among increase in data.

To further validate our contribution regarding the selection of the most discriminating sub-regions, we conduct another comparison. This comparison is concerned not only the RR obtained but also the size of the features vector, identification time and the total time of our recognition process. Table 4 shows this comparative study which is done using the division 7 and the same conditions as the first experiment.

Table 4: Comparison of the RR, the size of the features vector, the identification time and total execution time without and with selection of discriminating regions.

	Without Selection	With Selection
RR	96,98%	97,53%
Size of the features vector	2891	1416 for left hand 1121 for right hand
Identification Time	1,35 *s*	0,75 *s*
Total execution Time	2,4 *s*	1,8 *s*

As we have seen from these results, three interpretations can be drawn: the first is in terms of performance: an improvement gain of about 0,55% in RR, the second is in terms of storage space generated by the gain of more than half of size of features vector, and finally, the third is in terms of speed: a decrease in identification time and in total running time as half which is very interesting for real-time applications. The promising results of our approach have encouraged us to further test its performance over “PolyU-Palmprint” database. The following experimental result is achieved using 6438 palmprint images taken by 160 users (Table 5). Indeed, we used images taken from the 1st session as the gallery (3236 images) and images from the 2nd session as probe (3202 images) using the chosen division 7. When images of the palmprint are collected in two different sessions, several problems such as orientation, translation, texture deformation and lighting conditions vary from one session to another, which seems always the case in a real application. This experimental result can be one of the new experimental results published in the literature since the majority of work uses palmprint images are collected in the same session.

Table 5: Comparison of recognition rates with and without selection on “PolyU-Palmprint” databases.

	Without Selection	With Selection
Recognition rate	94,41%	95,35%

Although our approach is tested on a database with significant size using two different sessions which present more variability, the previous experience recorded an identification rate of 95,35% and we have once again shown the importance of the selection step with a gain of 0,94%.

3.3 Comparison with other Works

In this section, we compare our work with two of the most famous works in the literature, namely, the work of (Lu et al., 2003) and the work of (Wu et al., 2003). Table 6 presents the result of this comparison.

Table 6: Comparison of the obtained performance from the proposed approach and the work of Lu et al. and Wu et al.

Our approach	[Lu et al., 2003]
98,56%	99,14%
Our approach	[Wu et al., 2003]
98,83%	99,18%

It can be observed from the previous two experiments that the performance of our approach is slightly lower comparable to that of Lu et al. and Wu et al. Apart from the promising results, LBP has another big advantage over other methods which its simplicity in computation (Goh et al., 2008).

4 CONCLUSIONS

We have presented in this article a new approach for personal identification by palmprint. In the first place, lets say that the step of preprocessing is very important for contactless palmprint images and it is used to locate ROI from each individual hand. Then, a procedure of partitioning the whole image palmprint into sub-regions is achieved and the LBP operator is applied to describe the texture features within each subregion. In order to keep only the most discriminating regions for recognition, the SFFS algorithm has been the basis for this selection.

To validate our work and our contributions more precisely, we conducted several on-line experiments on two real databases with significant sizes "CASIA-Palmprint" and "PolyU-Palmprint". These experiments achieved a RR of 97,53% and 95,35% respectively on the two databases. The results obtained were satisfactory and show a considerable increase in RR with the selection of discriminating regions which prove the interest of our approach and also validate the choices made.

Our future orientation concerns the use of another solution for automatic segmentation of the hand to process images taken in a more complex environment.

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Portions of the work tested on the "PolyU-Palmprint" Database 2nd version collected by the Biometric Research Center at the Hong Kong Polytechnic University.

REFERENCES

Ahonen, T., Hadid, A., and Pietikainen, M. (2004). Face recognition with local binary patterns. In *Proceedings of the European Conference on Computer Vision(ECCV)*, pages 469–481.

CASIA-Palmprint-Database (2003). Casia palmprint database. http://www.cbsr.ia.ac.cn/english/Palmprint%20Databases.asp.

Chen, J., Zhang, C., and Rong, G. (2001). Palmprint recognition using crease. In *Proceeding International Conference on Image Process*, volume 3, pages 234 – 237, Thessaloniki , Greece.

Doublet, J., Lepetit, O., and Revenu, M. (2007). Contact less palmprint authentication using circular gabor filter and approximated string matching. In *Signal and Image Processing(SIP)*, volume 3, pages 495–500, Honolulu,United States.

Duta, D., Jain, A. K., and Mardia, K. V. (2002). Matching of palmprints. *Pattern Recognition Letters(PRL)*, 23(4):477–485.

Goh, M. K., Connie, T., and Teoh, A. B. (2008). Touchless palm print biometrics: Novel design and implementation. *Image and Vision Computing(IVC)*, 26(12):1551–1560.

Han, C. C., Cheng, H. L., Lin, C. L., and Fan, K. C. (2003). Personal authentication using palm-print features. *Pattern Recognition(PR)*, 36(2):371–381.

Kan, C. and Srinath, D. M. (2002). Invariant character recognition with zernike and orthogonal fourier-mellin moments. *Pattern Recognition(PR)*, 35(1):143–154.

Konukoglu, E., Yoruk, E., Darbon, J., and Sankur, B. (2006). Shape-based hand recognition. *IEEE Transactions on Image Processing*, 15(7):1803–1815.

Li, W., Zhang, D., and Xu, Z. (2002). Palmprint identification by fourier transform. *International Journal of Pattern Recognition and Artificial Intelligence(IJPRAI)*, 16(4):417–432.

Lu, G., Zhang, D., and Wang, K. (2003). Palmprint recognition using eigenpalm features. *Pattern Recognition Letters(PRL)*, 24(9-10):1463–1467.

Ojala, T., Pietikainen, M., and Maenpaa, T. (2002). Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. *IEEE Transaction on Pattern Analysis and Machine Intelligence(PAMI)*, 24(7):971–987.

Ojala, T., Pietikinen, M., and Harwook, D. (1996). A comparative study of texture measures with classification based on feature distribution. *Pattern Recognition(PR)*, 29(1):51–59.

Otsu, N. (1979). A threshold selection method from gray-level histograms. In *IEEE Transactions on SMC (Systems, Man, and Cybernetics)*, volume 9, pages 62–66.

PolyU-Palmprint-Database (2005). Polyu palmprint database. http://www4.comp.polyu.edu.hk/∼biometrics/.

Pudil, P., Novovicova, J., and Kittler, J. (1994). Floating search methods in feature selection. *Pattern Recognition Letters(PRL)*, 15(11):1119–1125.

Shapiro, L. and Stockman, G. (2001). *Computer Vision*. Prentice Hall.

Tana, X. and Songcan, C. (2006). Face recognition from a single image per person: A survey. *Pattern Recognition(PR)*, 39(9):1725–1745.

Wang, X., Gong, H., Zhang, H., Li, B., and Zhuang, Z. (2006). Palmprint identification using boosting local binary pattern. In *Proceedings of the 18th International Conference on Pattern Recognition(ICPR)*, volume 3, pages 503–506.

Wu, X., Zhang, D., and Wang, K. (2003). Fisherpalms based palmprint recognition. *Pattern Recognition Letters(PRL)*, 24(15):2829–2838.

Wu, X., Zhang, D., Wang, K., and Huang, B. (2004). Palmprint classification using principle lines. *Pattern Recognition(PR)*, 37(10):1987–1998.

Zhang, D., Kong, W., You, J., and Wong, M. (2003). Online palmprint identification. *IEEE Transaction on Pattern Analysis and Machine Intelligence(PAMI)*, 25(9):1041–1050.