Contact less palmprint authentication using circular Gabor filter and approximated string matching

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CONTACTLESS PALMPRINT AUTHENTICATION USING CIRCULAR GABOR FILTER AND APPROXIMATED STRING MATCHING

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ABSTRACT

More and more research have been developed very recently for automatic hand recognition. This paper proposes a new method for contactless hand authentication in complex images. Our system uses skin color and hand shape information for hand detection process. Next, the palm is extracted and characterized by circular Gabor filter. Finally, the palm features are matched by a new normalized approximated string matching. The experimental results present an error rate lower than 1.2% with a population of 49 people. We show that our method improves the performances of two palmprint methods 2D-Gabor and PPOC on our database.

KEY WORDS

Biometrics, Image Segmentation, Pattern Recognition, Color and Texture.

1 Introduction

Recently, biometrics recognition have attracted a lot of research and many works are reported in the literature. Biometrics technology is used to identify people from their physical or behavioral characteristics. These characteristics have three major specificities, they must be distinctive to differentiate each people, to be stable in the course of time and to be defined without a lot of constraints for users. So, various technologies were developed based on fingerprints, iris, face, voice, signature, gait or hand. Hand biometrics present many advantages compared to other biometrics technologies. Its characteristics are relatively stable and present a lot of discriminating features such as principal lines, wrinkles, ridges or hand shape. In addition, they present an high user acceptability and the hand can be obtained from low-resolution images with cheaper devices.

Many algorithms have been defined for hand authentication based on palmprint [1],[2],[3] or hand-shape recognition [4],[5]. All these algorithms can be decomposed in four stages: the acquisition, the hand segmentation (and palm definition if necessary), the features extraction and the comparison with the reference. Classically, the acquisition is a hand scan. Then, the hand is segmented by a fixed threshold and the palm is generally defined from hand shape curvature [2]. Next, various methods have been proposed for recognition. They are Sobel and morphological operations, Fourier spectrum, 2D Gabor phase [2], wavelet signatures [3], eigenpalm and eigenfingers features [6], phase and orientation code [7], etc. The last papers present really good results in recognition rate using generally a comparison method based on Hamming distance adjusted following the features. In all these systems, the hand acquisition is in fact the principal limit. It is not hygienic, all the users touch the same glass, and some artifacts can be created during the acquisition according to the pressure of users on the plate glass.

In this paper, we propose a contactless acquisition with a webcam to reduce these limitations and to get a quick and easy image acquisition. Hand detection process from these acquisitions is a complex task. Many methods are defined for hand detection in man-machine interactions like skin blob tracking, active contours, mean shift or condensation algorithm but provide an approximated detection of each finger. To increase the segmentation quality, we propose a method combining information of skin color and hand shape. This segmentation phase is described in section 2. In section 3, we defined a new feature extraction by circular Gabor filter and a novel palmprint matching using normalized approximated string matching. Section 4 contains some experimental results and section 5 provides the conclusions.

2 Preprocessing

Preprocessing is used to define the central part of the hand (the palm). The most part of preprocessing algorithm is decomposed in three steps. Firstly the hand is binarized by thresholding. Next, the contour of the hand is extracted and some key points are defined. Finally, from these points a coordinate system is defined and the palm is extracted. In our system, the architecture is kept but the methods are changed for a contactless system.

2.1 Accurate hand detection

In biometrics recognition systems, the first step consists on a definition of an accurate and fast segmentation process. In this section, we describe our hand detection method without tracking. This detection uses a fusion of skin color modeling and a robust active shape model.

2.1.1 Skin color segmentation

Classically the skin color is modeled by Bayes classifiers or Gaussian Mixture Models [8]. Contrary to these methods, our skin color is modeled by machine learning and for a good compromise between the execution time and the precision of detection, we use a neural network (NN). The NN entries are composed by three neurons, one for each color component of pixels in RGB domain. The NN output is the probability that a pixel is a skin pixel. The learning phase permits to model the skin tone in RGB domain. In parallel, a Principal Components Analysis on a skin pixels database defines a specific color space named skin space. After the learning, the NN can detect the pixels looking like skin. For each pixel of an image, the NN computes the probability that each pixel is a skin pixel. This process builds the probabilities map.
To obtain a segmentation close to real time, a multi-resolution process builds the probabilities map. This process computes the probabilities map at a lower resolution. Next the precision is increased in computing the probabilities only for the pixels near skin and non-skin transition in better resolution. Many methods are defined using the probabilities map to clearly identify the detected skin object (hand or face) and to get an accurate segmentation. The principal method consists in segmentation by histogram thresholding on the probabilities map [9, 10]. In our approach, a morphological dilatation with a circular element of radius one pixel is carried out on the probabilities map. Next, the probabilities map is segmented by histogram thresholding. This threshold is fixed to 0.5: each pixel is considered as skin color if the neural network output value is more that 0.5 else it is classified as background tone. Finally, as our hand detection process will be used for biometrics recognition, we suppose that only one hand is presented to the system. So the region with the largest surface is preserved and considered as the hand. The regions with an important size and elongation are so conserved. They can be some fingers disconnected from the hand for the users wearing some rings. To reconnect these regions to the hand, each preserved region is approximated by an ellipse and we search in the direction of the major axis if the hand is close. If the region is near the hand, an adjusted patch is added to reconnect the finger to the hand. This patch has a width equals to the width of the minor axis and a length depending on the distance between the finger and the hand. It is oriented with the major axis direction and centered between the hand and the finger. This process is illustrated in Figure 1.

(a) (b) (c)

Figure 1. Fingers re-connection: (a) binarized map (b) patch adjustment (c) binarized map with patch

2.1.2 Color active shape model

The segmentation by skin color cannot carry out the task of hand detection in a robust way. So, a specific active shape model is defined to cancel this problem and to solve the two major difficulties of active shape model [11]. These problems are the contour initialization which must be close to the real form and the model convergence in the detection phase.
Classically, the form to detect is defined by a set of points: the landmarks. In training phase, the average form and the contour variations are computed by principal components analysis on an hand database annotated by these landmarks. In segmentation phase, the contour is initialized by the characteristic points of the hand: the five fingertip points and the four points located in the valley between two adjacent fingers. These points are calculated from the skin segmentation by distance analysis on the contour. Next, two other points are automatically added close to wrist from these points. The other landmarks defining with more precision the hand shape are disposed between those. Thus, the model X is obtained by the 11 initial points and M intermediate points between those. X is defined by $\left[X[0], X[1], \ldots, X[(M+1) \times 10]\right]$ where $X[i]$ is the ith landmark. After the initialization phase, the model is deformed. To control the problem of model divergence implying that the model does not follow the real hand contours, a weight is applied to the deformations to limit the shape constraints. In addition, the gradient is computed in the skin color space by Di Zenzo algorithm. Next, this gradient is balanced by the coefficient of the probabilities map pixels. So the background objects do not perturb the contour evolution. The experiments show that a good compromise between the execution time and the detection precision is obtained by fixing M at 12. This complete detection process is illustrated on Figure 2(a-d).

2.2 Palm definition

After hand detection, it is necessary to define the palm independently of the distance between the hand and the capture device. Our extraction is based on hand dimensions and the palm extraction method described in [2]. In [2], two values are fixed: the distance between the points $O1$ and $O2$ and the palm size $||A1A2||$ (Figure 3). These constant values in traditional recognition systems are defined here according to hand sizes. They are determined from the hand width, computed by the Euclidean distance between the points $X[L1]$ and $X[L2]$ where $L1$ and $L2$ are the indexes fixed after experiments at 30 and 125. Thus, $||O1O2||$ and $||A1A2||$ are defined by:

$$\begin{cases} ||O1O2|| &= \alpha||X[L1]X[L2]|| \\ ||A1A2|| &= \beta||X[L1]X[L2]|| \end{cases} \tag{1}$$

Where α and β are the dimension coefficients chosen at $1/10$ and $2/3$, respectively. Next, the palm is resized with a fixed size $N \times N$.
The extracted palm contains some principal lines which can be determined by a specific palm line extraction. These lines are not unique to each individual, thus it is necessary to use the ridges and the secondary lines of the palm. This information cannot be extracted from the palm with images in low resolution, so a global palm characterization is suitable.

3 Robust circular Gabor filter

The Gabor filter is a well known tool in texture analysis. The Gabor filters are a gaussian modulated by a wave. In oriented Gabor filters, this wave is an oriented complex sinusoidal signal. A typical formula expression is:

$$G(x,y) = g(x,y) \times \exp\Big(2\pi i f\big(x\cos\theta + y\sin\theta\big)\Big) \tag{2}$$

$$\text{where } g(x,y) = \frac{1}{2\pi\sigma^2}\exp\left(\frac{-(x^2+y^2)}{2\sigma^2}\right) \tag{3}$$

The parameters f and θ represent the frequency and the orientation of the sinusoidal signal respectively. $g(x,y)$ is a Gaussian with the scale parameter σ. The Gabor filters have an important specific quality: they provide an accurate

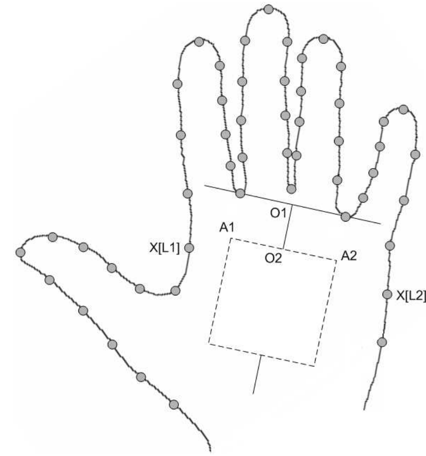


Figure 3. Schematic palm extraction with $M = 4$

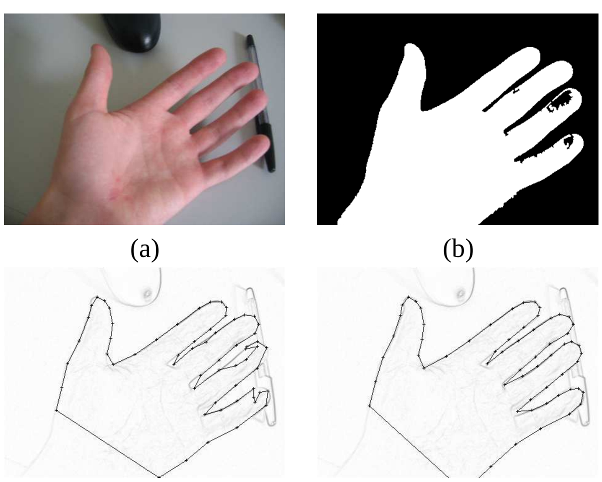
time and frequency location. In addition, they are robust to variation of brightness and contrast. So, these filters have been used with very high recognition rate in multiple biometrics applications with fingerprints, iris [14] or palmprint [2]. Recently, the performances of palmprint recognition using Gabor filters have been improved using a combination of different orientation filters [7]. In this paper, the palm features are extracted by a circular Gabor filter. This filter is a Gaussian modulated by a circular wave. So, this filter can be defined as [12]:

$$G_c(x,y) = g(x,y) \times \exp\Big(2\pi i f\sqrt{x^2+y^2}\Big) \tag{4}$$

where f is the frequency of the circular Gabor filter and $g(x,y)$ is defined by (3). The real part of oriented Gabor filter and circular Gabor filter with $f = 0.3666$, $\sigma = 1.4045$ and $\theta = 0°$ (for oriented filter) are shown in Fig. 4. For more luminosity robustness, the filter is turned to zero DC (direct current). So, a robust circular filter of size $(2n+1)^2$ can be explained by:

$$\Omega_c(x,y) = G_c(x,y) - \frac{\sum_{i=-n}^{i=n}\sum_{j=-n}^{j=n} G_c(i,j)}{(2n+1)^2} \tag{5}$$

This robust circular Gabor filter is convoluted with the palm image to product the palmprint features. Contrary to the methods of Zhang and al. [2][7], the features are not binarized so all information is kept. With all information, the variation between two data is preserved. So for example, two pixel values -0.001 and $+0.001$ that are really close are not considered very different contrary to a binary matching based on negative or positive values.



(a) (b) (c) (d)

Figure 2. Hand detection (a) original image (b) skin segmentation (c) initial hand shape (d) final hand shape

4 Normalized approximated string matching

From the features, many methods are employed like energies computation, Euclidean distance or some pixel based comparison (as Hamming distance) if the features are binarized. In our method, an approximated string matching

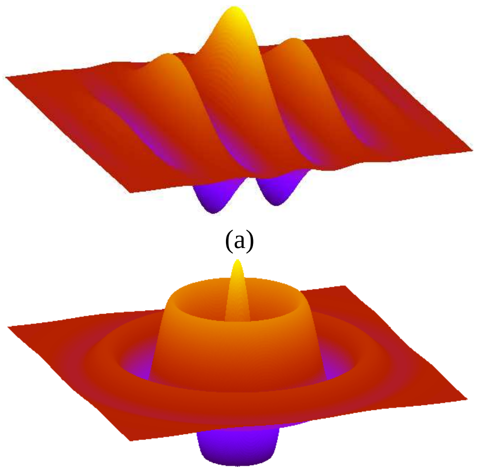


Figure 4. Oriented (a) and circular (b) Gabor function

algorithm (AMSA) described by Hoad [13] in another context is used to match our features.

4.1 Approximated string matching

AMSA is based on Levenshtein distance which is a generalization of Hamming distance. Initially, the AMSA permits to compare two vectors in computing a scoring matrix with a scoring function. This function determines the similarity between two elements. The scoring matrix is filled following a match or a mismatch between the elements of the vectors. The matching score is the high value in scoring matrix. The AMSA is robust to translation, deletion, substitution or addition of elements in the vectors. The algorithm 1 presents the matrix filling where T is the threshold defining match or mismatch, $f_1(d)$ is the match scoring function and $f_2(d)$ is the mismatch scoring function. The algorithm have two vectors V_1 and V_2 of size s_1 and s_2 respectively in input. In Table 1, an example of matrix filling for two vectors $V_1 = \{8, 3, 11, 32, 21, 7, 6, 15, 20\}$ and $V_2 = \{11, 31, 20, 7, 1, 15\}$ with the parameters $T = 1$, $f_1(d) = 4$ and $f_2(d) = 6$ is shown. In this example, the scoring matching between V_1 and V_2 is equal to 16. The functions f_1 and f_2 can be complex and depend of the difference d in Algorithm 1.

	V1	8	3	11	32	21	7	6	15	20
V2	0	0	0	0	0	0	0	0	0	0
11	0	0	0	4	0	0	0	0	0	0
31	0	0	0	0	8	2	0	0	0	0
20	0	0	0	0	2	12	6	0	0	4
7	0	4	0	0	0	6	16	10	4	0
1	0	0	0	0	0	0	10	4	0	0
15	0	0	0	0	0	0	4	0	8	2

Table 1. Scoring matrix example

Algorithm 1: Approximated string matching algorithm

Input: Two Sets $V_1[1, \ldots, s_1]$ and $V_2[1, \ldots, s_2]$, a threshold T, a match scoring function f_1 and a mismatch scoring function f_2.
Output: Scoring matrix M between the two sets.

begin
  Initialization;
  Scoring matrix $M[0 \ldots s_1, 0 \ldots s_2]$
  for $i \leftarrow 0$ **to** s_1 **do**
    $M(0, i) = 0$
  end
  for $j \leftarrow 0$ **to** s_2 **do**
    $M(j, 0) = 0$
  end
  Matrix computation;
  for $i \leftarrow 1$ **to** s_1 **do**
    for $j \leftarrow 1$ **to** s_2 **do**
      $d = ||V_1(i) - V_2(j)||$
      if $d \leq T$ **then**
      $M(i, j) = M(i-1, j-1) + f_1(d)$
      else $M(i, j) = Max\big(0, M(i, j-1) - f_2(d), M(i-1, j) - f_2(d)\big)$
    end
  end
end

4.2 Palmprint matching

The matching procedure is applied on vectors. So, a palmprint feature P which is the real and imaginary part of the convolution of the robust circular Gabor filter with the palm is represented as a vector of size $S = N \times N \times 2$. We propose to modify the definition of the matrix computation to increase the weight of long matching sequence between two vectors. So, the definition of the matrix computation is changed by a function using the last calculated scores. To compare two palmprint features P_1 and P_2, we used the Algorithm 2 where $f_1(x, d) = x \times 2 + 1$ is the match scoring function and $f_2(x, d) = x/2$ is the mismatch scoring function. The coefficients functions are fixed for a very quick execution. Sure without constraints, the coefficients of these functions can be fixed following the difference d.

The maximum value of scoring match is $2^{S+1} - 1$. So, a normalized distance between two palmprint features P_1 and P_2, where the perfect matching is 0 and the poorest matching is 1, is defined by:

$$D(P_1, P_2) = 1 - \max_{\substack{0<i\leq S \\ 0<j\leq S}} \big(M(i, j)\big)/(2^{S+1} - 1) \qquad (6)$$

Algorithm 2: Palmprint matching algorithm

Input: Two palmprint features $P_1[1,\ldots,S]$ and $P_2[1,\ldots,S]$, a threshold T, a match scoring function f_1 and a missmatch scoring function f_2.
Output: Scoring matrix M between the two sets.

```
begin
    Initialization;
    Scoring matrix M[0...S, 0...S]
    for i ← 0 to S do
        M(0, i) = 0
    end
    for j ← 0 to S do
        M(j, 0) = 0
    end
    Matrix computation;
    for i ← 1 to S do
        for j ← 1 to S do
            d = ||P1(i) − P2(j)||
            if d ≤ T then
            M(i, j) = f1(M(i − 1, j − 1), d)
            else M(i, j) =
            f2(Max(M(i, j−1), M(i−1, j)), d)
        end
    end
end
```

5 Experimentations

A specific database is made to validate our approach. All images of the database were acquired by a webcam *Philips ToUcam Pro 740K* with a size of 640×480. The database contains 490 images of hands, some of these presenting hands with rings, coming from 49 people. 10 images are acquired for each individual of the database. The capture restrictions are that the users must present their hands in front of the camera with theirs fingers separated. The users are not accustomed to the system, so in practice, a bad acquisition is automatically rejected by the system. On this database, the proposed method is compared to two systems of Zhang and al.: 2D Gabor filters [2] and PPOC [7]. For these two methods, the palms size is 128×128 to form $DB1$ and for our method the palms size is 32×32 named $DB2$ to limit the computation and the reference size. Figure 5 shows two examples of hand images with corresponding palm in $DB1$. Each palm in the database is compared with all the other palm images. To increase the robustness of the system and limit the impact of inaccurate hand detection, five palms are used as enrollment. So, to compare two palmprint features P_1 and P_2, four features of the same user that the second feature are randomly added to the second one to form a test set $\{P_2^1, \cdots, P_2^5\}$ with $P_2^1 = P_2$. The matching distance is a defined by the minimum matching score between the palmprint features:

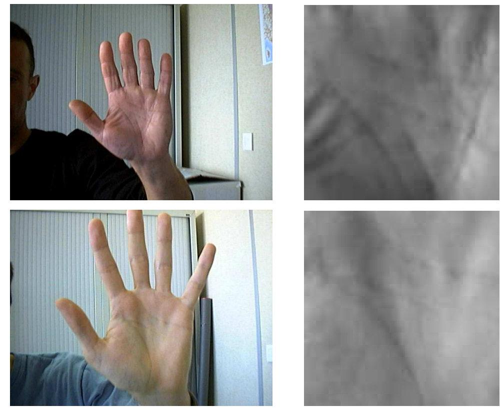
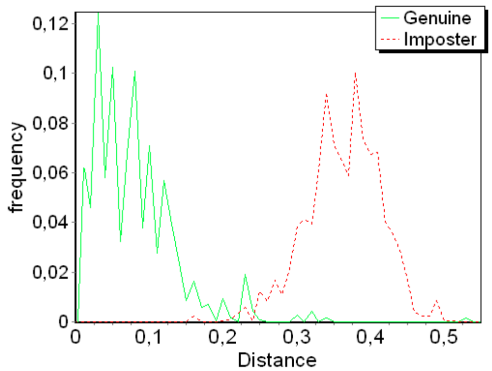


Figure 5. Two examples in our database and corresponding palm from DB1

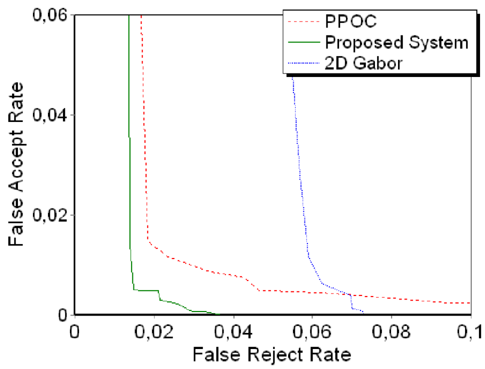
$$D_f(P_1, P_2) = \min_{1 \leq i \leq 5} D(P_1, P_2^i) \tag{7}$$

To limit the random impact, the total comparison process is done 10 times. So, the total number of comparison is 1202950. From the comparison process, the distance matching distribution curves are defined. These curves represent the frequency of matching score between the references coming from the same user named the genuine curve and coming from two different users named the impostor curve. These curves are showed in Figure 6 (a).

From a matching $D_f(P_1, P_2)$, a threshold δ must be fixed to defined if the two compared features P_1 and P_2 come from the same users or not. So, if the matching score is lower than the threshold δ then the two features come from the same user else they are declared as coming from two different users. A comparison is incorrect if a user is accepted or rejected wrongly. Two rates characterize the accuracy of the system: the false acceptance rate (FAR) defined by the ratio of people authenticated wrongly and the false rejection rate (FRR) defined by the ratio of people rejected wrongly. The proposed method based on circular Gabor filter and string matching is evaluated with a set of parameters. So, the optimal parameters obtained are $f = 0.0916$, $\sigma = 5.6179$ and $T = 0.25$. The corresponding optimal comparison rate on $DB2$ is presented in Figure 6 (b) and shows an equal error rate (when FAR=FRR) equals to 1.2%. Finally, our system is compared to the methods of Zhang and al. 2D-Gabor filters [2] and Palmprint Phase and Orientation Code (PPOC) [7] with optimal parameters and five palms as enrollment. The optimal results presented in table 2 show that our system outperformed the methods of Zhang and al. in our database. The complete process of recognition (segmentation, characteristics extraction and matching) is carried out in less than 1 second on Pentium M with 1.60GHz.



(a)



(b)

Figure 6. Authentication test results: distance matching distribution (a) and ROC (b)

Method	2D-Gabor	PPOC	Proposed method
EER	5.8%	1.7%	1.2%

Table 2. Comparison of systems proposed by Zhang and al. and our method

6 Conclusions

In this paper, we present a new method of biometrics hand recognition for a contactless system. First of all, the hand segmentation is explained. It is carried out thanks to an integration of the skin color components and a shape model. Then, the authentication process based on circular Gabor filter and robust string matching is exposed. The features extraction permits to get the information in all directions in a limited time. Next, the modified string matching computes a distance robust to a limited bad palm extraction and noisy images. The complete process is validated after experiments on a database of 49 people. It shows an error rate of 1.2% with an execution time lower than 1 second.
In order to manage space rotation of the hand, an invariant method with the perspective and the shear will have to be required. Moreover, the test database will have to be diversified and supplemented to confirm our approaches. These two tracks are currently the subject of our work.

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