BIOMETRIC VERIFICATION USING CONTOUR-BASED HAND GEOMETRY AND PALMPRINT TEXTURE

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ABSTRACT
Hand biometrics is extensively used for personal authentication in the recent years. This paper focuses on two hand biometric traits, namely, hand geometry and palmprint. We propose a method to use hand contour as a feature vector for hand geometry. The novelty of our approach is the implicit capturing of the individual features (like finger lengths, widths) in a single entity of hand contour. The sequence information of the contour is then fed to a hidden Markov model classifier. For palmprint the feature vector used for classification is the texture energy measure. Texture provides a high-order description of the local image content. The texture analysis is based on the well documented Laws' convolution masks. Linear and Gaussian kernel support vector machines are employed as classifiers. Both these approaches are validated by experimental results.

KEY WORDS
Biometrics, hand geometry, palmprint, Support Vector Machine (SVM), Hidden Markov Model (HMM), texture energy.

1. Introduction

Biometrics deals with the automated identification of individuals, based on recognizable traits. The traits can be physiological, such as facial features, fingerprints, iris, palmprint and hand geometry; or behavioral such as voice, gait, signature and handwriting. These traits can be used individually (single mode) or in combination (multi-mode) depending on the security level of the application. For a trait to qualify as a biometric, it must be universally distinct, permanent, robust and acceptable to the user. In the identification task, the system decides who the user is, while in the verification task, it verifies his claimed identity. In this paper, we treat verification as a binary classifier problem (Accept/Reject).

Hand based biometrics is non-invasive in nature. Two independent modalities are derivable from a hand image - hand geometry and palmprint. Hand geometry based system exploits measurable features like palm area, lengths and widths of fingers and hand shape. Hand geometry is distinctive enough for verification but not for identification [1]. The system works well even with a low resolution image. Further, it can be easily integrated with other hand biometrics like fingerprints and palmprint. Hand geometry schemes in the literature are mostly based on distinctly measurable features. Ref. [1] proposes a peg-based imaging scheme for hand geometry. Ref. [2] measures finger heights and widths at different latitudes and the angles of the inter-finger valleys with the horizontal.

Palmprint is made up of principal lines, wrinkles, minutiae and delta points. It also consists of many wrinkles whose pattern is well characterized by texture. Palmprint analyses using Gabor filters [3], wavelets [4] and local texture energy [5] have been proposed in the literature. An attempt has been made to estimate palmprint crease points by generating a local gray level directional map [6].

In this paper, we explore traits like the shape of the hand contour (rather than measurement-based hand geometry), and palmprint texture as potential biometric verifiers. We probe different classifiers, namely hidden Markov models for hand shape in Section 2 and support vector machines for palmprint texture analysis in Section 3. The experimental details are provided in Section 4.

2. Contour-Based Hand Geometry

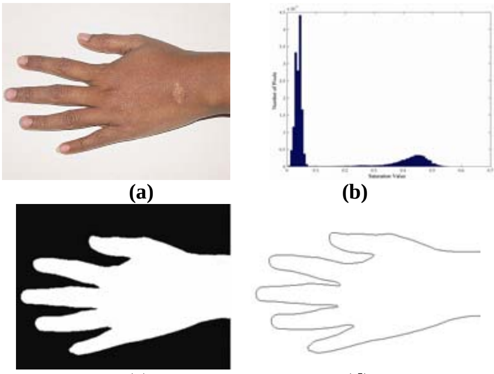
The aim of the hand geometry based biometric system is to capture the uniqueness of the shape of an individual's hand. In this section we describe an approach to extract feature vector from hand geometry. We propose a method that exploits the intrinsic information present in the shape of the hand by using hand contour as a feature.

Various hand placements for image capture: We define three types of hand placement for the image capture. Maximum, intermediate and minimum positions of the hand are depicted in Fig. 1(a), (b) and (c) respectively. Minimum position images are used for palmprint extraction only. The images collected for multiple positions of the hand are helpful in capturing some variability in the examples.

(a) (b) (c)
Fig. 1. Hand images acquired in (a) maximum (b) intermediate and (c) minimum positions

2.1 Detection of hand contour

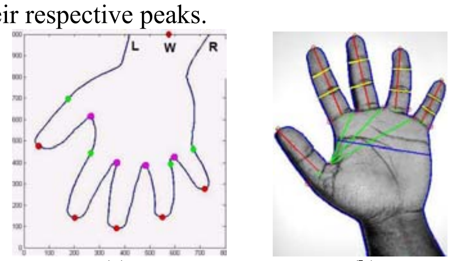
The image of the hand obtained in RGB format is transformed to HSV space and a saturation value of 0.1 is used for the thresholding operation. The gray scale image is then fed to the Canny's edge detection algorithm [7]. Output is an image showing the positions of tracked intensity discontinuities. Any breaks in the edge are connected by the line-following algorithm. The morphological operation of dilation and erosion are used. The contour trace forms the sequence of observation symbols from an edge image.



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

Fig. 2. (a) Input image (b) Histogram showing the separation between two peaks – hand & background saturation values (c) Binary image with threshold at 0.1 (d) Edge image using Canny's Algorithm

Salient points: To measure the various hand geometry features, the "landmark points" [8] like fingertips (peaks) and valley points have to be located as shown in Fig. 3(a). The wrist reference *W* is the midpoint of the bottom-left pixel *L* and the bottom-right pixel *R*. The distance between *W* and each point on the contour of the hand from *L* to *R*, is measured [9]. A plot of distance for different points on the contour has peaks and valleys corresponding to the local maxima and local minima alternately. For each of thumb, fore finger and little finger, a valley point opposite to the existing one is plotted, assuming that the two valleys are equidistant from their respective peaks.



(a) (b)

Fig. 3. (a) Salient points (b) Finger lengths, finger widths and palm width measures of the hand extracted in measurement-based hand geometry

Limitations of measurement-based hand geometry: The measurement-based biometric works on the assumption that no two persons have the same set of finger/palm lengths and widths in the same order. The various length measures shown in Fig. 3(b) forms the feature vector of a person. Though this method works satisfactorily for hand geometry verification, we observed the following limitations:

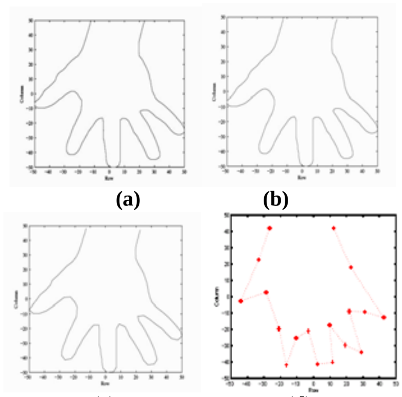
1. The uniqueness which is intrinsic in the contour (shape) of the hand as a whole is not captured. This approach, usually employed in verification tasks, is not suitable for identification purposes because of the incompleteness of the feature vector.
2. The lengths and widths of fingers are sensitive to the noise in boundary pixels as well as to the scaling factor of the image.
3. The position of wrist reference *W* is dependent on the placement of the hand. Methods to plot maximum curvature points [10] as peaks and valleys eliminate the need for *W*. But as we observed, this method is as sensitive to the noise as the previous one.

Above mentioned limitations are overcome in the proposed contour based approach. We describe the method in the following section.

2.2 Classification of contours using HMM

The hand contour is obtained from the image as explained in previous section. The length of a contour varies from one person to another; typically a person with larger hands will have a longer contour. Hidden Markov Model classifier is well suited for handling such varying length patterns which can be characterized as a sequence. We use the sequence of edge pixel coordinates as the feature vector for the contour.

During the data acquisition, the various positions of the hand of the same person are captured. For the generation of a large number of examples of his hand contour, the images collected in maximum and intermediate positions are used. The inclusion of minimum-position images does not improve intra-class variability (The number of states of the HMM shown in Fig. 4(d) is 20). Continuous-density HMMs with one mixture for each state are used.



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

Fig. 4. Contour traces at (a) Original (b) 1/7th (c) 1/15th resolution (d) Means of observation points for 18 states of HMM using (a).

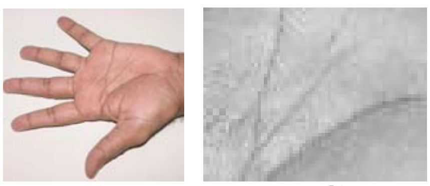
Generation of training samples: For training the HMM, a reasonable number of samples are required. Synthetic examples are generated by sub-sampling the original hand contour. The accuracy of the system is not compromised since this system does not impose any high demands on resolution. Two subsequences are generated from the original sequence by considering the even and odd numbered observation points (edge pixels) respectively. Three more subsequences are generated from the original vector by considering every third pixel (i.e. {first, fourth, seventh …}, {second, fifth, eighth, …}, {third, sixth, ninth, …} pixel co-ordinates and so on). In a similar manner four sub-samples of one-fourth the resolution are derived. The minimum resolution used in our work was *1/15* of the original. Refer Fig. 4(a)-(c). Thus we get one sample of original resolution, two samples of half the original resolution, and three samples with one-third of the original resolution and so on, to get ${}^{15}\Sigma_{j=1}(j) = 120$ samples. Finally the multiple contour traces obtained are used to train a hidden Markov model classifier.

Interpretation of HMM states: The HMM model thus generated gives the mean and variance for each of the states. To get an insight as to what these states depict, we plot the means of the states. Among the 20 states, the first and last states are dummy states and the remaining 18 states are as shown in Fig. 4(d). It is observed that the states correspond to the salient points that define hand shape. The probability of occurrence of a state is high in a region where there is an observable change of shape in the contour. In Fig. 4(d), we notice that each of the salient points like the finger peaks and valleys has a corresponding HMM state associated with it. Hence we claim that the geometry information of the hand is implicitly captured in these states.

It should be noted that we have not used measurement of finger/palm to derive these states. This makes the method independent of the scaling factor of the image and the placement of the hand. The user gets a greater flexibility in placing his hand before the camera. Moreover, the inherently distinctive hand geometry (as observed by the naked eye) is captured accurately.

3. Palmprint Texture

The palmprint is regarded as one of the most unique, reliable, and stable personal characteristics, and performs effectively as a biometric. We describe the extraction of the region of interest and building a texture energy map in this section.



(a) (b)

Fig. 5. At a resolution of 50 X 70 (a) Hand image (b) Extracted palm RoI

Palm Region of Interest (RoI): The palm RoI [11] is taken as a rectangle of height to base ratio 5:7. The height of the rectangle is the line joining the valley between fore and middle fingers, and the valley between ring and little fingers. After obtaining the outline of the RoI, the image is cropped and rotated to make the base horizontal as in Fig 5(b). The image is then resized to *50 X 70* pixels.

3.1 Feature selection from palm RoI

In this paper, texture feature measurement is used as a technique for palmprint. Texture provides a high-order description of the local image content. This method is a modified approach based on [12]. A feature called the texture energy is computed using Laws' convolution masks [13] which is found to have good discriminating information. This statistical approach pioneered by K I Laws is computationally simple. He introduced the concept of local texture energy E, evaluated at each pixel location *(i, j)* in the convolved image over a large window size *15 X 15* as the measure of the texture features in the spatial domain.

The fixed masks lack of robustness and are replaced with adaptive masks tuned to be robust to the classification tasks. This process involves the determination of the texture using tuned mask. These masks (when applied to a textured image) smoothen out regions of common texture so that the variance of the convolved image over a window is: (a) reasonably constant in the region of uniform texture, (b) sufficiently varying between regions of different textures.

The four tuned masks that capture the texture energy are sensitive to horizontal lines, vertical lines, 45^0 and -45^0 lines respectively. The masks are given in [12]. The local variance after convolution is well approximated by the sum of squared values of the convolved image within the test window.

$$C_k = I * M_k$$

where I is the image, * is the convolution operator, C_k is the convolved image, obtained after convolving the input palmprint image with the mask M_k.

Texture Energy map: The texture energy measure, E at a pixel *(i, j)* has been defined in [12] as

$$E[i,j] = \frac{\sum_u \sum_v C_k{}^2[u,v]}{P^2 W_x W_y}$$

where $W_x \times W_y$ is the averaging window dimension,

$$i - \frac{W_x}{2} \le u < i + \frac{W_x}{2},\ i - \frac{W_y}{2} \le v < i + \frac{W_y}{2},$$

$$P^2 = \sum_i \sum_j M_k{}^2[i,j]$$

This texture energy measurement is insensitive to noise and has good intra-class convergence and inter-class dispersion. The texture energy map is the matrix E and is directly used as the feature vector to train support vector machines (SVM) for classification. Thus we get four different classifiers namely horizontal (H), vertical (V), diagonal one (D1) and diagonal two (D2) corresponding to 0^0, 90^0, 45^0 and -45^0 lines respectively. The edges detected in the convolved images are manifested as peaks in the texture energy map. The edges given in the convolved output are of a higher gray value. These are amplified by squaring (and normalizing) as per the computation given in (2).

3.2 Classification using SVM

The reasons for using the SVM classifier are two-fold. Firstly, the input feature vectors are fixed length patterns. The number of training samples is very small, typically 18 samples per class. Secondly, SVMs can handle high dimensional input vectors and therefore their use is appropriate in image processing problems. In our work for example, the texture energy map, which is used as a feature vector, is of dimension 3500 (*50 X 70* pixels) for palmprint. In such problems, even if it is not clear what the features are, the user can represent the image as a vector of gray values.

Texture energy map as a feature vector: We observed that the texture energy map at a resolution of *50 X 70* pixels is a good feature as it gave a high interclass variability and low intra-class variability. Two examples are available per person obtained from maximum and intermediate positions. In the intermediate position, extra wrinkles are added to the palm due to the fact that the fingers are brought closer to one another. Extra lines are especially visible near the area joining the thumb and the palm. The SVM model is able to capture these variabilities.

The output of convolution for an example image of Fig. 5 is shown in the Fig. 6. Due to the low intra-class variability and high inter-class variability as illustrated in Fig. 7, the SVM classifier is able to perform the classification with good accuracy.

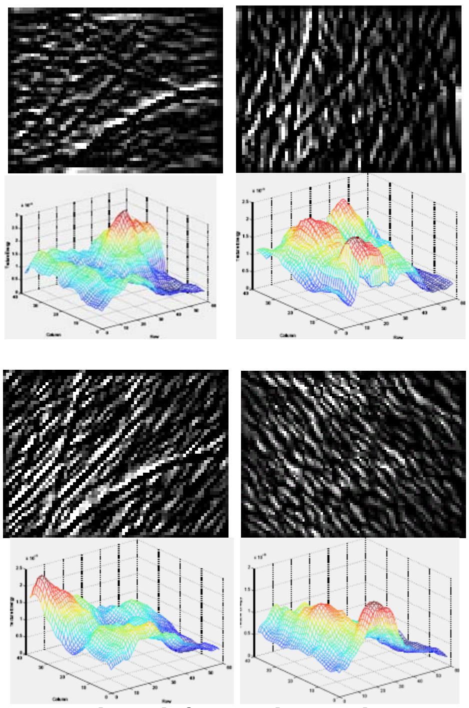
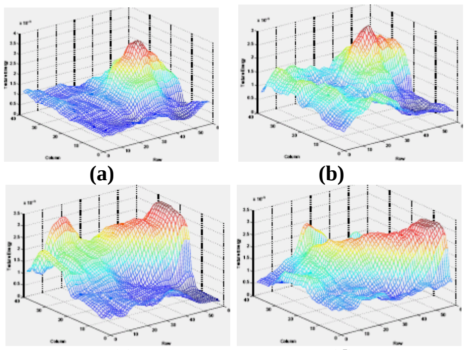


Fig. 6. Images obtained after convolution with H, V, D1 & D2 masks with their corresponding TE maps below them.



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

Fig. 7. TE Maps for Person 1 at (a) Maximum (b) Intermediate positions. TE Maps for Person 2 at (c) Maximum (d) Intermediate positions. Low intra-class variability is seen between the TE maps of (a) and (b), (c) and (d). High "inter-class" variability is seen between the TE Maps of (a) and (c).

Training and testing data: The total number of samples in our data set was 35. Out of 35, due to improper placement of hand 5 samples were discarded and experiments were performed on the remaining 30 samples. From the two positions, namely maximum and intermediate position, 18 palmprint images were generated per class (person). A total of 9 examples were derived per position. The first 8 were derived by down-sampling the original palmprint image. This was done by interleaving as described below:

Sub-sampled Image 1: First, ninth, seventeenth… rows and columns.
Sub-sampled Image 2: Second, tenth, seventeenth … rows and columns.
…
Sub-sampled Image 8: Eighth, sixteenth, twenty fourth… rows and columns.
The ninth image of a particular position was obtained by reducing the image to one-eighth the size using bilinear interpolation.

The input feature vectors are extracted from the training set, preprocessed and normalized before giving to the SVM. Appropriate kernel is selected and the respective SVM model is generated. For testing, the normalized feature vector of the test example is given to SVM and the output of SVM is used for verification.

4. Experimental Results

In this section, we provide the details of our image acquisition scheme and results obtained from the approaches described above for hand geometry and palmprint.

Image acquisition setup: A digital camera (Model: Sony, MVC-CD100, 3.3 mega pixel resolution) was used to capture hand images at a resolution of *560 X 400* pixels. The camera was mounted on a tripod, approximately one foot in height, in face down position. The users were asked to place their hands on a flat surface. The background was chosen as white to improve separability from the foreground which is of skin color. The images were taken in a controlled lighting environment. The above hand image acquisition scheme is peg-free i.e. the user need not place his/her hand within the constraints of pegs.

4.1 Hand geometry: Performance of HMM classifier

As explained in Section 2.2, 120 samples were derived per position per class. 95 samples were used for training and 25 were kept for testing. In the process of sub-sampling, hand contour vectors of 15 levels of resolution were obtained. In the set of 25 samples for testing, one example of each resolution was kept. Table 1 shows how the performance of the HMM classifier varies with the chosen number of states. This study was done on the samples obtained from the maximum position. The experiment was conducted for number of states varying from 5 to 20. For number of states as 7 or more the HMM classifies with an accuracy of over 98 percent. The optimal number of states to represent hand geometry is approximately 7. For number of states less than 7, the classification performance sharply reduces.

Table 1. Performance of HMM classifier for different number of states (in max. position)

Number of states	Misclassification rate (%)
20	0
10	0
7	2
5	10

Table 2. Performance of HMM classifier for different hand positions

Training samples	Testing samples	Misclassification rate (%)
Maximum	Maximum	0
Intermediate	Intermediate	1
Maximum & Intermediate	Maximum & Intermediate	0.9
Maximum	Intermediate	75
Intermediate	Maximum	82

Another study was done to assess the ability of the HMMs to capture the variations in the position of the hand during image acquisition. We observed that when samples from maximum position were used for training and samples from intermediate position were used for testing, the performance was poor. When the training samples were taken from both maximum and intermediate positions, the classification performance was good. The testing samples were chosen arbitrarily. Of the 120 samples, 95 were used for training and 25 for testing. The results are given in Table 2.

4.2 Palmprint: Performance of SVM classifier

The 18 examples obtained per class as explained in Section 3.2 were divided in two sets for the purpose of training SVMs and testing the data. The two sets were obtained as shown in Table 3.

Table 3. Grouping of examples for training and testing

Data Set	Training Examples	Testing Examples
One	6 (1. . . 5, avg)	3 (6. . . 8)
Two	7 (1. . . 6, avg)	2 (8, avg)

Table 4. Performance of palmprint based system for data sets One and Two (Maximum and Intermediate positions).

Model	Set 1- Misclassification rate (%)		Set 2 - Misclassification rate (%)	
	Gaussian Kernel	Gaussian Kernel	Linear Kernel	Linear Kernel
H	1.075	1.075	1.3	2.419
V	1.075	1.075	0.0	0.8065
D1	1.613	1.613	0.230	1.613
D2	6.98	6.98	2.07	5.645

One-against-the-rest SVM was used for classification. The SVM was built using Linear and Gaussian kernels. The results for data set “One” and data set “Two” are as shown in Table 4. The training and testing data was obtained from both the maximum and intermediate positions. The standard deviation parameter for the Gaussian kernel was empirically chosen as $\sigma = 0.1$. The value of the trade-off parameter C was set as 1 (default in the SVMTORCH package used is 100). We observed that each of the models namely H, V, D1 and D2 perform equally well. This indicates that as far as palmprint texture is concerned, the edges in all the four directions are equally indicative and uniquely characterize the palmprint. The Gaussian kernel performs marginally better than the linear kernel. The input feature vector dimension is high; hence linear SVMs are also capable of separating the classes.

5. Conclusion

This paper studies two hand biometric traits, hand geometry and palmprint. Based on the promising experimental results, we conclude that the suggested schemes are viable for human authentication. HMM potentially exploits the sequence information of the hand contour. The features extracted from palmprint are robust enough as far as scalability is concerned.

The algorithm for hand geometry system can be made robust to variations in the positions of the hand by considering individual contours for the four fingers and the thumb. This feature vector will be insensitive to the position of hand during image acquisition. Palmprint method can be modified for smaller feature vectors typically 30 X 30 which is very commonly used for online identification of faces. We are presently studying the finger texture (like ridges, inner knuckle texture) as a possible biometric trait to supplement the palmprint. The analysis of finger RoI can be similar to that of palm RoI. Multi-modal hand biometrics is also being explored taking hand geometry, palmprint and finger texture into consideration.

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