Orientation Map Based Palmprint Recognition

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A new palmprint recognition method based on the orientation maps was proposed. The model consists of a method for extracting distinctive features from palmprint images that can be used to perform reliable matching. From the palmprint obtained using the CCD camera, the candidate significant points are detected by examining at different scales and its magnitude is used as a measure to identify its significance. For each significant point, we work out the descriptor which comprise of vector made of values from the convolved orientation maps located on concentric circles centered on the significant point, and where the extent of Gaussian smoothing is relative to the radii of the circles. Experiments have been conducted on the standard PolyU palmprint database. Experiments show that the newly proposed method provides higher recognition rate compared to other similar models.

KEYWORDS: Orientation maps, Local descriptors, Palmprint recognition.

Introduction

Biometric based identity establishment is a well-established means of technology in the society. Over the past decade, among the many other biometric traits, palmprint recognition has been examined in detail [5]. The imageries of human palmprints are found to be relatively stable and unique [2]. As the acquisition of palmprints take little co-operation from the individuals, palmprint modality is gaining popularity in recent days especially in the applications of access control [5].

Till now only few works have been stated on palmprint biometrics compared to the other biometric modalities. Many global and local features are used for this purpose. Recently Mu et. al. [7] used complex directional wavelet and local binary pattern as a shift and gray scale invariant features for palmprint identification. Template based palmprint identification is proposed by Yue et. al. in [12]. In [14], Zhang et. al used Gabor features for online palmprint verification. Zhang et al [13] used 2D Gabor features and 3D surface curvature map to achieve robust palmprint verification.

It is observed that the palmprint images highly differ with respect to illumination which are captured in two different sessions [9]. Also images are geometrically transformed. To address this issue some authors ([1], [4] or [2]) proposed local descriptor based systems. In [1] and [4], authors used SIFT [6] features for palmprint verification, whereas in [2], Badrinath et. al. used SURF for palmprint verification. In this paper, we propose a local descriptor based palmprint recognition model where the significant points are described by the vector of orientation maps composed from its neighborhood region.

Methodology

The proposed palmprint recognition involves following modules: *preprocessing of original palmprint image, significant point extraction using SURF detector, descriptor computation for each significant point* and *descriptor matching.* These are explained briefly in the remaining part of this section. Figure 1 shows the framework of proposed palmprint recognition model.

Preprocessing. The raw palmprint image consists of parts from the finger in addition to whole palmprint image. Also the boundary regions of the palm are more sensitive to the intensity

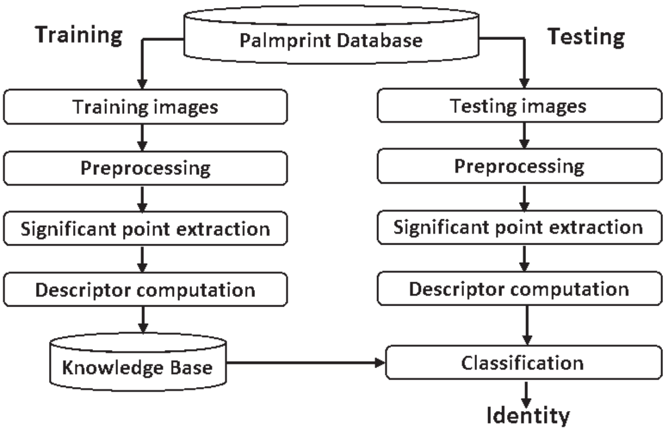
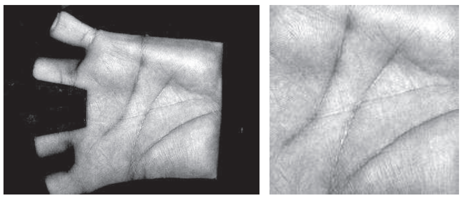


Fig. 1. Palmprint recognition framework.

changes. To eliminate the unwanted regions preprocessing is required. Figure 2(a) shows the original palmprint image. The preprocessing consists of getting the region of interest(ROI) which consists of the central part of the palmprint. The raw palmprint is binarized in the first stage which eliminates the background region and results only the regions from the palm including fingers. Then we identity largest square region which is inside the palm outline. The central region of size 171×171 is extracted as the ROI, which is the result of preprocessing stage and used for locating the significant points. Figure 2(b) shows the preprocessed palmprint image.



(a) (b)

Fig. 2. Original palmprint image and ROI extracted image from PolyU palmprint database [9].

Significant point extraction. The significant points are extracted by means of SURF detector [3]. It uses the determinant of the Hessian matrix. For a point $p = (x, y)$ in image I, the Hessian matrix $H(p, \sigma)$ is the matrix of partial derivatives of the image I, in the following form,

$$H(p,\sigma) = \begin{bmatrix} L_{xx}(p,\sigma) & L_{xy}(p,\sigma) \\ L_{xy}(p,\sigma) & L_{yy}(p,\sigma) \end{bmatrix} \tag{1}$$

where $L_{xx}(p, \sigma)$ is the convolution of the Gaussian second order derivative with the image I in point p, and similarly for $L_{xy}(p, \sigma)$ and $L_{yy}(p, \sigma)$. Its discrete formations are used in actual implementation. The first two diagrams in Figure 3 shows discrete Gaussian second order derivative.

The Hessian matrix is computed by the box filters which in turn uses integral images to speed up the operation. These box filters approximates the second order Gaussian derivatives. The 9×9 box filters in Figure 3 are approximations of a Gaussian with $\Sigma = 1.2$ and represent

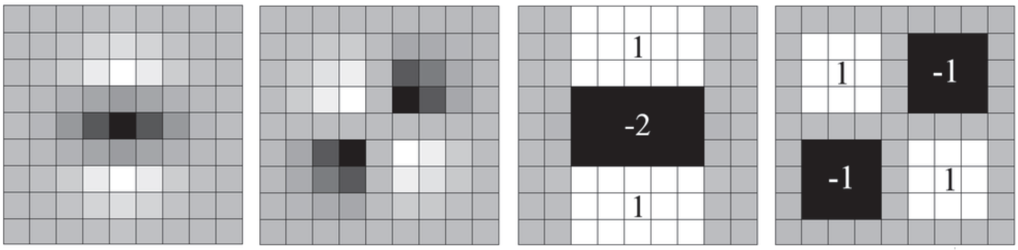


Fig. 3. The first two images represent the discretised Gaussian second order partial derivative in y (L_{yy}) and xy direction (L_{xy}) respectively. The last two images represent the approximation for the second order Gaussian partial derivative in y (D_{yy}) and xy direction (D_{xy}). The gray regions assumed to be zero. (Image Courtesy [3])

the lowest scale for computing the blob response maps. Suppose D_{xx}, D_{yy} and D_{xy} are the approximations to I_{xx}, I_{yy} and I_{xy}, the determinant of H_{approx} is computed as,

$$det(H_{approx}) = D_{xy}D_{xy} - (wD_{xy})^2 \tag{2}$$

where w is the weight of the filter response used to balance the expression for the Hessian's determinant. The approximated determinant of the Hessian represents the blob response in the image at location p. For a given image, the likely significant points are identified by searching at all scales and based on the strength of the likely significant point, final significant points are extracted. The scale space construction followed by the non-maximum suppression in the neighborhood is performed. The maxima of the determinant of the Hessian matrix represents the significant point in the given palmprint image

Descriptor Computation. Significant point descriptor computation is similar to descriptor which was introduced by Tola et al. in [11] for matching stereo images. In our work, for all significant points, we compute the descriptor which comprise of vector of values from the convolved orientation maps located on concentric circles centered on the significant point, and where the amount of Gaussian smoothing is relative to the radii of the circles. Significant point descriptor building process comprises of three stages: *computing orientation maps, convolving orientation maps with Gaussian kernels,* and *forming significant point descriptor*. For all significant points in the image I, we first compute orientation maps in different directions. Orientation map $G_i(u,v)$ for the significant point (u,v), equals the image gradient at (u,v) in the direction i, if it is greater than zero else it is equal to zero. $G_i = (\delta I/\delta i)^+, 1 \leqslant i \leqslant H$, where H is the total orientation maps and $(.)^+$ is the operator such that $(a)^+ = max\,(a,0)$. Each orientation map is then convolved with Gaussian kernels of different Σ values to obtain convolved orientation maps for different sized regions as $G_i^{\Sigma} = G_{\Sigma} * (\delta I/\delta i)^+$with G_{Σ} a Gaussian kernel. Different Σs are used to control the size of the region. This can be done efficiently by computing these convolutions recursively. Figure 4 and Equation 3 shows these computations.

$$G_i^{\Sigma_2} = G_{\Sigma_2} * (\delta I/\delta i)^+ = G_{\Sigma} * G_{\Sigma_1} * (\delta I/\delta i)^+ = G_{\Sigma} * G_i^{\Sigma_1} \tag{3}$$

where $\Sigma = \sqrt{\Sigma_2^2 - \Sigma_1^2}$ and $\Sigma_2 > \Sigma_1$. The descriptor for every significant point is computed by gathering the values from the convolved response maps from its neighborhood. As depicted in Figure 5, at significant point location, say (u,v), descriptor consists of vector of values from pixels located on concentric circles and their amount of Gaussian smoothing is relative to the radii of these circles. Let $h_{\Sigma}(u,v)$ be the vector made up of the values at location (u,v) in the convolved response maps.

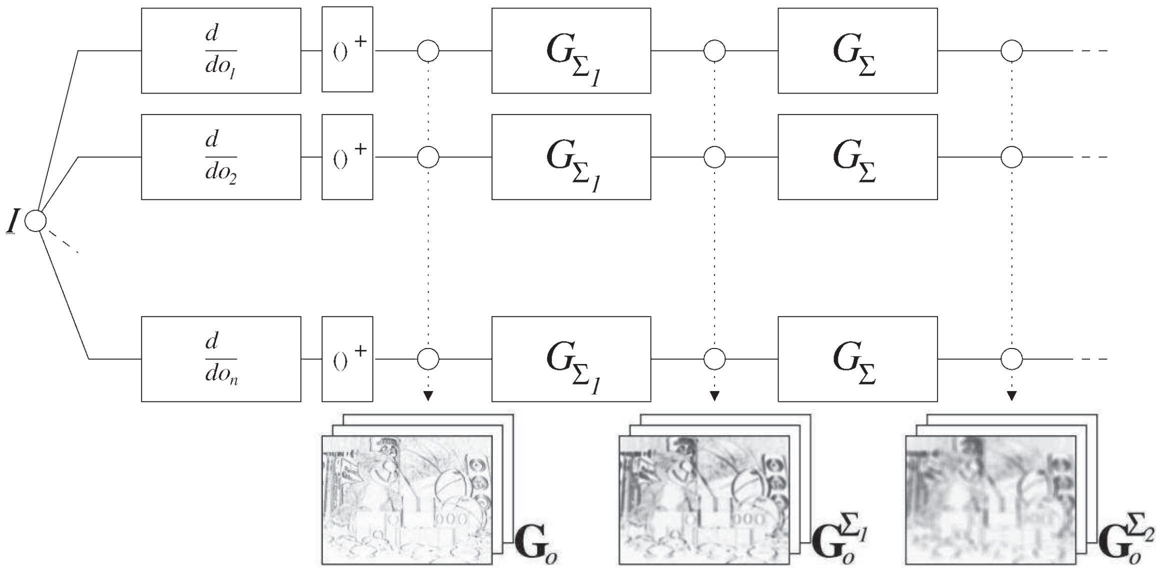


Fig. 4. Original image (I), Orientation maps (G_o) and Convolved orientation maps ($G_o^{\Sigma_i}$). (Courtesy [11])

$$h_\Sigma(u,v) = \left[G_1^\Sigma(u,v), G_2^\Sigma(u,v), ..., G_8^\Sigma(u,v)\right]^T \tag{4}$$

where $G_1^\Sigma, G_2^\Sigma, ..., G_8^\Sigma$ denote the Σ convolved response maps.

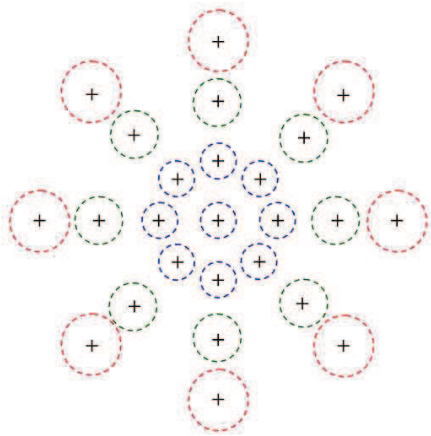


Fig. 5. Shape of the sampling locations of the descriptor. The '+' sign indicates the sampling locations. The radius of the dashed circle represents the size of the Gaussian kernel. (Courtesy [10])

Before concatenating these vectors to a descriptor, we normalize them to unit vector, and denote the normalized vectors by $\tilde{h_\Sigma}(u,v)$. The full descriptor D(u,v) for the significant point location (u,v) can be can be written as:

$$
\begin{aligned}
D(u,v) = [&\tilde{h}^T_{\Sigma_1}(u,v), \\
&\tilde{h}^T_{\Sigma_1}(I_1(u,v,R_1)), ..., \tilde{h}^T_{\Sigma_1}(I_N(u,v,R_1)), \\
&\tilde{h}^T_{\Sigma_2}(I_1(u,v,R_2)), ..., \tilde{h}^T_{\Sigma_2}(I_N(u,v,R_2)), \\
&... \\
&\tilde{h}^T_{\Sigma_Q}(I_1(u,v,R_Q)), ..., \tilde{h}^T_{\Sigma_Q}(I_N(u,v,R_Q))]^T
\end{aligned}
\tag{5}
$$

where $I_j(u, v, R_1)$ is the location with distance R from (u, v) in the direction given by j when the directions are quantized into N values. Figure 5 shows the sample locations when N = 8, and significant point descriptor is made up of values extracted from 25 locations and 8 response maps. Therefore, descriptor length is 200 (i.e. 8×25).

Descriptor Matching. Two images are matched using the descriptors of their corresponding significant points. The match score between two images X and Y is the total number of significant points matched between two images. For every point from image X, the best and second best matching points of the image Y was found by finding the euclidean distance between corresponding descriptors. If the best match is much better than the second best, points are said to be alike. Equation 6 shows how to apply such condition, where points b and c in palmprint image Y are the best and second best matches, respectively, for point a in the palmprint image X. The threshold was found by the emperical analysis.

$$
\frac{\left|D^a_X - D^b_Y\right|}{\left|D^a_X - D^c_Y\right|} < threshold \tag{6}
$$

Experimental Results

This section describes the palmprint database and evaluation of results.

Palmprint Database. We conducted the experiments using PolyU palmprint database [9]. It contains 7752 gray scale images corresponding to 386 persons acquired using a CCD camera in the controlled environment. The images are captured in two sessions with an average interval of two months. In our experiments, we used a subset of PolyU palmprint database, consisting of first 100 individuals, having 10 samples in the first session and 10 in the second.

Experiments and Results. The experiments are carried out with different number of training samples ranging from 1 to 5. For each of these experiments, we used 4000 testing samples with different combination of the training and testing samples including alternate/continuous captured images. The average number of significant points in the image is found to be 65. We used the samples from the first session for training and samples from the second session for testing, as it is more realistic in nature. The recognition accuracy with varying number of training samples is given in Table 1. As expected, the recognition accuracy increases as the number of training samples increases. We have also provided a comparative study with well known SIFT descriptor which is designed for palmprint recognition[1,4]. The recognition rate in SIFT based recognition varies a little for the change in number of training samples. This may be due to the fact that the number of points matched in SIFT is comparatively less.

Conclusion

In this paper we proposed a new palmprint recognition framework based on the significant points which is described by orientation maps. The model gives robust results for small change

Table 1. Comparison of recognition accuracy of the proposed model with local descriptor based techniques.

Method used	Training samples per individual				
	5	4	3	2	1
Proposed Model	83.93	81.70	78.75	73.85	63.45
SIFT	60.50	60.05	60.70	58.50	50.65

in illumination and geometric transformation. The experimental results show that proposed model works better than other local descriptor based representations. Future work involves finding more robust descriptors for the representation of the significant points.

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