Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 2 (2010) 159–163

Procedia Computer Science

www.elsevier.com/locate/procedia

ICEBT 2010

Motion invariant palm-print texture based biometric security

Rohit Kumar* , Ratnesh P. Keshri, C.Malathy, Annapoorani Panaiyappan.K

Department of Computer Science and Engineering, SRM university, Chennai

Abstract

Biometric based identification is an emerging technology that can solve many security problems. Although systems based on fingerprint and eye features have so far achieved the best matching performance, human hand also contains a wide variety of features, e.g. shape, texture and principal palm lines etc. This feature of the human hand is quite stable and hand images can be extracted very easily. Palm-print is a new and emerging biometric feature for personal recognition. This paper describes an automated approach to palm-print recognition. In contrast to existing palm-print based biometric systems, a new system which is resistant to motion variance of the palm has been proposed. A Palm-print image is taken as an input and then a low pass Gaussian filter is applied to remove the noise from image. Further, since the centre of mass always remains constant, so this property has been taken into account to extract the ROI (Region of Interest) from palm-print image. SIFT (Scale Invariant Feature Transformation) features have been used further for extracting stable texture features from the ROI and are stored. These stable features extracted from the ROI are further used for comparison with stable texture features extracted from ROI of other palm-print images to provide biometric based identification and security.

Keywords: ROI; SIFT; Gaussian

1. Introduction

More than a century has passed since Alphonse Bertillon first conceived and then industriously practiced the idea of using body measurements for solving crimes (Rhodes, 1956). Biometric recognition refers to the use of distinctive physiological (e.g., fingerprints, face, retina, iris, palm print) and behavioral (e.g., gait, signature) characteristics, called biometric identifiers (or simply biometrics) for automatically recognizing individuals. Perhaps all biometric identifiers are a combination of physiological and behavioral characteristics and they should not be exclusively classified into either physiological or behavioral characteristics. For example, palm-prints may be physiological in nature but the usage of the input device (e.g., how a user presents palm to the palm-print scanner) depends on the person's behavior. Thus, the input to the recognition engine is a combination of physiological and behavioral characteristics. The whole paper has been sub divided into four modules that is Palm-print acquisition where palm images are taken as input. Further next stage is Palm-print preprocessing where Low pass Gaussian filter has been used to filter the images before extracting the ROI. Filter is applied to remove the noise present in image. ROI is extracted by finding center of mass of palm-print and then a suitable rectangular ROI is taken. The next stage is Texture Feature Extraction where SIFT [1] [11]has been employed for extracting the stable key points. The stable key points that are invariant to scale and orientation are derived on the basis of Gaussian function to identify potential interest points that are invariant to scale and orientation. Further the final stage is Texture feature matching where using the key points extracted from ROI, Point wise matching has been performed further to match the palm images. Public database of palm-print images provided by Hong Kong Polytechnic University (PolyU) Palm-print Database [7] has been taken and used for testing of the results. This database contained palm images from 386 samples which had been taken in two sessions each session with a gap of two month.

* Corresponding author. Tel.:+91-9884396282;.
E-mail address: rohitraz@gmail.com.

doi:10.1016/j.procs.2010.11.020

2. Prior-Work

There are many palm-print based recognition system existing where hand geometry, principal palm lines, hand texture or fusion of finger print and hand geometry, fusion of hand geometry and principal palm line etc have been used. Also, most researcher have focused on palm-print based security using 2D or 3D wavelet , Filters but system is still not resistant to motion variance of palm caused while scanning palm images. Some of the novel approach like use of Gabor Filters [3], SIFT [1] features for Palm-print feature extraction have formed basis for research by many.

3. Methodology

The system development has been divided into four modules.

3.1 Palm-print Acquisition
This stage requires acquisition of palm-print image. We have used online database provided by The Hong Kong Polytechnic University (PolyU) Palm-print Database. The Biometric Research Centre (UGC/CRC) at The Hong Kong Polytechnic University has developed a real time palm-print capture device, and has used it to construct a large-scale palm-print database. The PolyU Palm-print Database [7] contains 7752 grayscale images corresponding to 386 different palms in BMP image format. Around twenty samples from each of these palms were collected in two sessions where around 10 samples were captured in the first session and the second session, respectively. The average interval between the first and the second collection was two months.

3.2 Palm-print Processing
The palm-print processing has been done to obtain a sub image of the palm-print from the axis drawn along the center of mass of palm-print. This sub image taken removes the rotational and translation variations. The processing of image requires following steps:

Low pass filter have been applied to the original image. Gaussian Filter has been used as low pass filter to avoid noise. The equation for the Gaussian [2][3] low pass filter is

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

where x is the distance from the origin in the horizontal axis, y is the distance from the origin in the vertical axis, and σ is the standard deviation of the Gaussian distribution. Noise is avoided to get the correct value of centre of mass of palm image.

Further the image has been converted to binary image using a threshold value. Mathematically, this transformation can be represented as

$$B(x; y) = 1 \quad \text{if} \quad O(x; y) * L(x; y) \geq Tp \tag{2}$$

$$B(x; y) = 0 \quad \text{if} \quad O(x; y) * L(x; y) < Tp \tag{3}$$

Where B(x; y) and O(x; y) are the binary image and the original image, respectively; L(x; y) is a low pass filter, such as Gaussian, and "∗" represents an operator of convolution. The threshold value has been decided by performing various iterations so that some of the noise also gets removed. The threshold value taken is 0.1.

3.2.3 Centre of mass is extracted from this binaries palm-print image. The centre of mass is found by summing the co-ordinates of binaries image where ever intensity is 1 along X and Y axis and then dividing each sum individually by product of sum of X and Y co-ordinates where ever intensity was 1 to find centre of mass along X and Y axis

3.2.4 Further based on the center of mass a sub image has been extracted from palm-print by drawing a fixed rectangular coordinate along it. The coordinate for the rectangular sub image is defined mathematically as

$$X_{\min} = X_{\text{cm}} - C_x \tag{4}$$

$$Y_{\min} = Y_{\text{cm}} - C_y \tag{5}$$

$$X_{\max} = X_{\text{cm}} + C_x \tag{6}$$

$$Y_{\max} = Y_{\text{cm}} + C_x \tag{7}$$

Where C_x and C_y are constants. Hence, these steps have been performed to extract the ROI from palm image.

3.3 Texture Feature Extraction

Image matching is a fundamental aspect of many problems in computer vision, including object or scene recognition SIFT[1] (Scale Invariant feature Transform) method have been used for feature extraction. The features extracted using SIFT are invariant to image scaling and rotation, and partially invariant to change in illumination and 3D camera viewpoint. They are well localized in both the spatial and frequency domains, reducing the probability of disruption by occlusion, clutter, or noise. Large numbers of features can be extracted from typical images using SIFT with efficient algorithms. In addition, the features are highly distinctive, which allows a single feature to be correctly matched with high probability against a large database of features, providing a basis for object and scene recognition. This approach has been named the Scale Invariant Feature Transform (SIFT), as it transforms image data into scale-invariant coordinates relative to local features. An important aspect of this approach is that it generates large numbers of features that
densely cover the image over the full range of scales and locations. A typical image of size 500x500 pixels will give rise to about 2000 stable features (although this number depends on both image content and choices for various parameters).

Following Steps have been performed to find texture feature of an image.

3.3.1 Scale-space extrema detection

In this stage the scales and locations on image which have stable features have been searched. This has been implemented by finding difference of Gaussian surface to identify potential interest points that are invariant to scale and orientation. The first stage of key point detection has been identifying locations and scales that can be repeatedly assigned under differing views of the same object. Detecting locations that are invariant to scale change of the image has been be accomplished by searching for stable features across all possible scales, using a continuous function of scale known as scale space .It has been shown by Koenderink (1984) [8] and Lindeberg(1994) [4] that under a variety of reasonable assumptions the only possible scale-space kernel is the Gaussian function. Therefore, the scale space of an image is defined as a function, L(x, y, σ), that is produced from the convolution of a variable-scale Gaussian, G(x, y, σ), with an input image, I(x, y).

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \quad (8)$$

Where * is the convolution operation in x and y.

To efficiently detect stable key point locations in scale space, we have proposed [2] using scale-space extreme in the difference-of-Gaussian function convolved with the image, D(x, y, σ), which can be computed from the difference of two nearby scales separated by a constant multiplicative factor k

$$\begin{aligned} D(x, y, \sigma) &= G(x, y, K\sigma) - G(x, y, \sigma) * I(x, y) \\ &= L(x, y, K\sigma) - L(x, y, \sigma) \end{aligned} \quad (9)$$

There are a number of reasons for choosing this function. First, it is a particularly efficient function to compute, as the smoothed images, L, need to be computed in any case for scale space feature description, and D can therefore be computed by simple image subtraction. In addition, the difference-of-Gaussian function provides a close approximation to the scale-normalized Laplacian of Gaussian, σ^2 ^2G, as studied by Lindeberg (1994)[9].Lindeberg showed that the normalization of the Laplacian with the factor σ^2 is required for true scale invariance. In detailed experimental comparisons, Mikolajczyk (2002) [10] found that the maxima and minima of σ^2 ^2G produce the most stable image features compared to a range of other possible image functions, such as the gradient, Hessian, or Harris corner function.

3.3.2. Key point localization

Key points are selected based on measures of their stability. At each candidate location, a detailed model is fit to determine location, scale, and ratio of principal curvatures. This information allows points to be rejected that have low contrast (and are therefore sensitive to noise) or are poorly localized along an edge.

3.3.3. Orientation assignment

One or more orientations are assigned to each key point location based on local image gradient directions. All future operations are performed on image data that has been transformed relative to the assigned orientation, scale, and location for each feature, thereby providing invariance to these transformations.

3.3.4. Key point descriptor

The local image gradients are measured at the selected scale in the region around each key point. These are transformed into a representation that allows for significant levels of local shape distortion and change in illumination.

3.4 Texture Feature Matching and Recognition

For image matching and recognition, SIFT features had been first extracted from a set of reference images and stored. A new image has been matched by individually comparing each feature from the new image to the previous stored feature and finding candidate matching features based on Euclidean distance of their feature vectors. Further In this stage based on the key-point descriptor that is generated using SIFT feature the images have been compared. If D1 and D2 are the two descriptor of the images to be matched then descriptor D1 is matched to a descriptor D2 only if the distance d (D1, D2) multiplied by threshold is not greater than the distance of D1 to all other descriptors. The default value of threshold is 1.5.

4. Results

4.1. Experimental Result

Palm-print Image was given as an input (Fig 1). The first step was converting this image in binaries format (Fig 2). Further from this binaries image , image coordinates where extracted and then centre of mass of image was found (Fig 3).Using this centre of mass ROI have been extracted (Fig 4) and further this ROI was given as an input to SIFT which gave detailed descriptor, this descriptor was used to compare the ROI to find matches. The plot of ROI which matched (Fig. 5) and which did not matched (Fig. 6) shows the stable points or potential interest points which have been selected from ROI found using finding difference of Gaussian surface. The line in this plot (Fig. 5 and Fig. 6) is drawn among the points which matched in the two ROI of palm-print image.

4.2. Test Result

Testing was performed by matching different set of images of a same person and different person. The total no of test cases taken were on 386 samples [7]. Around twenty samples from each of these palms were collected in two sessions where around 10 samples were captured in the first session and the second session, respectively. The average interval between the first and the second session was two months. The accuracy achieved was around 97% that is out of 7720 total images taken 6948 images gave correct result. Also the average processing time on core 2 duo processor found was near about 2second to find whether the images matched or not.

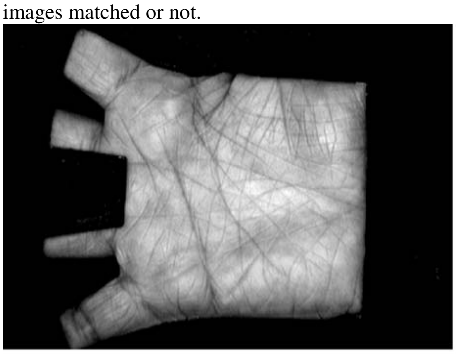

Fig. 1 Digital image

Fig. 2 Binaries Image

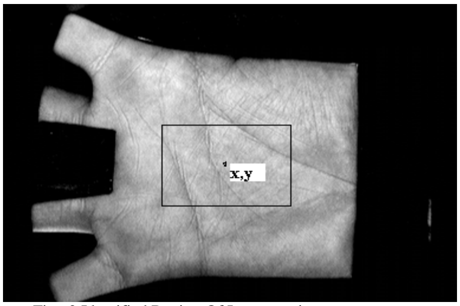

Fig . 3 Identified Region Of Interest using co-ordinate. of center of mass of palm image.

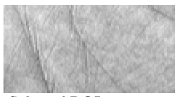

Fig.4 Selected ROI

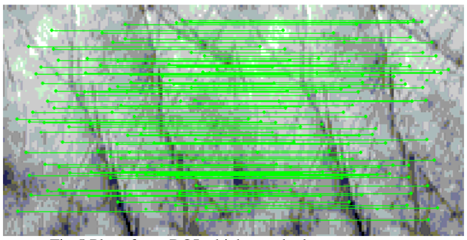

Fig.5 Plot of two ROI which matched.

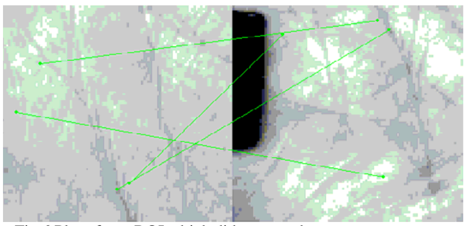

Fig.6 Plot of two ROI which did not match.

5. Conclusion

In this paper we presented a novel approach to motion invariant palm-print based biometric security and in future improvement can be done in processing time. Also efficiency and accuracy would be improved by applying better filter like Gabor filter and use of 2D-wavelets or 3D- wavelets instead of Gaussian filters. Multimodal approach would also give a better secured system in future.

6. References

[1] Jiansheng Chen, Yiu-Sang Moon "Using SIFT Features in Palm-print Authentication (IEEE 2008)"
[2] Deng, G. Cahill, L.W. Dept. of Electron. Eng., La Trobe Univ, Bundoora, "An adaptive Gaussian filter for noise reduction and edge detection (IEEE Explore 1993)".
[3] Wai Kin Kong, David Zhang, Wenxin Li " Palm-print feature extraction using 2-D Gabor Filters (The journal of Pattern Recognition Society in the year 2003)".
[4] Kluwer Academic Publishers Hingham, MA, USA **"**Edge Detection and Ridge Detection with Automatic Scale Selection(International Journal of Computer Vision)".
[5] W. Shu, D. Zhang, "Automated personal identification by palmprint ", Opt. Eng. 37 (8) (1998) 2659–2662.
[6]"Digital Image processing Using MATLAB (Second edition)" By Rafael C.Gonzalez
[7] The Hong Kong Polytechnic University, PolyU Palmprint Database, www.comp.polyu.edu.hk/biometrics.
[8] Koenderink, J.J. 1984. The structure of images. Biological Cybernetics, 50:363-396.
[9] Lindeberg, T. 1994. Scale-space theory: A basic tool for analysing structures at different scales.Journal of Applied Statistics, 21(2):224-270.
[10] Mikolajczyk, K. 2002. Detection of local features invariant to affine transformations, Ph.D. thesis, Institut National Polytechnique de Grenoble, France.
[11] David G. Lowe "Distinctive Image Features from Scale-Invariant Keypoints" (International Journal of Computer Vision, 2004)