Peg Free Multi-Dimensional Palmprint Feature Extraction Using Hybrid Level Fusion Strategy

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(Received on 14 April 2012 and accepted on 15 October 2012)

Abstract – **This paper presents a new personal authentication system that simultaneously exploits 2D and 3D palm print and geometrical features of the hand. The geometrical features are obtained from the binaries images by using Otsu's threshold technique. Multimodal (2-D and 3D) palm print and hand geometry features, which are simultaneously extracted from the user's textured 2-D and 3-D hand, are used for matching. Individual matching scores are then combined using a new Hybrid level fusion strategy. The objective of this work is to improve accuracy and robustness of existing palm print authentication systems using combination of the 2D and 3D palm print features. A peg-free system is composed by a pc and camera. The users put the hand in free space in front of the camera. The hand is illuminated by an infra- red light to solve segmentation problems in a real environment. The surface curvature feature based method is investigated for Gabor feature based competitive coding scheme is used for 2D representation.**

The database of 120 subjects achieved significant improvement in performance with the integration of 2D and 3D palm print and hand geometry features. Such as those mounted on a laptop, mobile device, and web camera or those for surveillance, can dramatically increase the applicability of such a system. However, the performance of existing techniques for palm print authentication falls considerably, when the camera is not aligned with the surface of the palm.

The experimental results also suggest that the Hybrid level fusion approach employed in this work helps to achieve the performance improvement of 70% (in terms of EER) over the case when matching scores are combined using the Dynamic fusion approach.

Keywords: **Biometrics, Peg Free Palm Print, Gabor Features, Dynamic Fusion, 2D Palm Print, 3D Palm Print, Hybrid Level Fusion**

I. Introduction

Automatic recognition of individuals based on their physical and/or behavioral characteristics Possible confirm or establish an individual identity based on 'who he/she is? Rather that 'what he / she possess'. Biometric personal identification is emerging as a powerful means for automatically recognizing identities. It concerns with identifying people by their physiological characteristics such as iris pattern, retina, palm print, fingerprint, hand geometry and face or some behavioral aspects such as voice, signature and gesture. The use of digital imaging, specifically camera based imaging, for biometric authentication has changed the applicability of biometric authentication for personal security. Camera based imaging is fast, inexpensive, convenient to use, and is easily available to the common man. In addition to biometric modalities such as face, gait, etc., one can employ camera based imaging for fingerprints, palm prints, or even handwriting. Real Time Online Palm print matching was made possible with the use of electronic imaging by capturing low resolution images using devises such as web cameras [2]. The hand is illuminated by an infra-red light to solve A palm print image contains various features, including principal lines, wrinkles, ridges, minutiae points, singular points and texture.

Lines and texture are the most clearly observable features in low-resolution palm print images a line contains various information, including 1) type, 2) width, 3) position, 4)magnitude and 5) orientation. There are two types of lines: positive and negative [4]. Lines and texture are the most clearly observable features in low-resolution palm print.

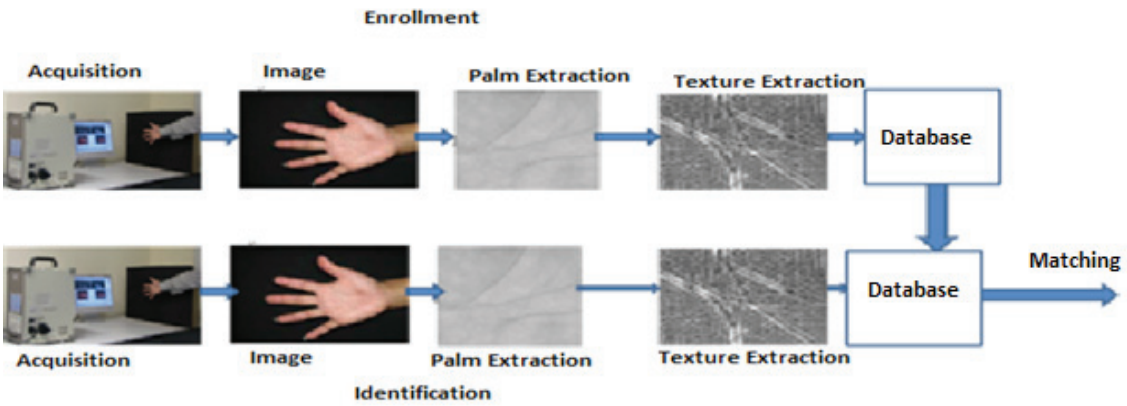

Fig. 1 Palmprint Recognition System

Images segmentation problems in a real environment. Various technologies were developed such as fingerprint, iris, face, voice, signature and hand. This last method is based on a study of hand shape and texture. It has many advantages compared to other technologies. Firstly, the capture device is less expensive than that for iris recognition; the hand characteristics are more numerous than those of fingerprints and they can be specified with low resolution images. Moreover, this system is well accepted by the users [3]. Most of the existing hand involved techniques require pegs or contact-based image acquisition devices.

This causes some increasing user acceptance issues and system reliability issues. In this paper we propose a contact-free biometric system based on the hand geometry. A contact-free system is composed by a pc and a camera. The users put the hand in the free space in front of the camera. In these systems there are two main tasks to solve: classify the palm print features into three different levels: shape level, line level and texture level. Shape features are contained in 3D palm print and they are at the coarsest level. Principal line features exist in both 2D and 3D palm print images and they are at the second level, which represent the structural information of palm print principal lines. Texture features are also contained in both 2D and 3D palm print images and they are at the finest level, which represent the detailed features of palm print. Intuitively, the texture information is well suited for palm print discrimination. 3D palm print recognition techniques have been recently developed [7], where the 3D Palm print data are captured by using structured-light imaging [8]. In the 3D palm print system the depth information of the palm inner surface is collected, and a curvature-based method is used for 3D palm print feature extraction and matching. Since the 2D and 3D palm print images can be captured simultaneously, the 2D and 3D palm print features can be readily fused. Some straightforward fusing methods were used and better results than using 2D or 3D features only were obtained. Hybrid fusion strategy to selectively combine the 2D and 3D palm print features extracted from the pose corrected 3D and 2D hand. It is working with low resolution sensors. It is low cost sensors compared to the other biometric traits sensors. Ability to Operate in Challenging Environments Established, Reliable Core Technology Relatively stable physiological characteristic the rest of this paper is organized as follows. Section II provides a detailed description of our approach for 2D Palm print feature extraction. Section III gives a Brief review of 3D palm print features extracted from the pose corrected range and intensity images. The Hybrid fusion strategy for combing match scores from 2D palm print and 3D palm print matchers is detailed in Section III, Section IV and V introduce the 2D and 3D and database and present experimental results.

II. 2D Palm Print Feature Extraction

A. Implementation of Otsu Algorithm (Binary Image)

In this module used to binarizing the intensity image using Otsu's threshold the first preprocessing step is to localize the hand in the acquired hand images (Fig 2). Since the intensity and range images of the hand are acquired near simultaneously, these images are registered and have pixel to pixel correspondence. Therefore, to localize the hand by binarizing the intensity image using Otsu's threshold [10]. In Otsu's Threshold an optimal threshold is selected by the discriminant criterion, so as to maximize the reparability of the resultant classes in gray levels. From the viewpoint of discriminant analysis, this system directly approaches the feasibility of evaluating the goodness of threshold and

automatically selecting an optimal threshold. First the gray-level histogram is normalized. And dichotomize the pixels into two classes by a threshold at level. The Procedure is utilizing only the zero- and the first-order cumulative moments of the gray-level histogram. Here, use the stand point. This standpoint is motivated by a conjecture that well threshold classes would be separated in gray levels, and conversely, a threshold giving the best separation of classes in gray levels would be the best threshold.

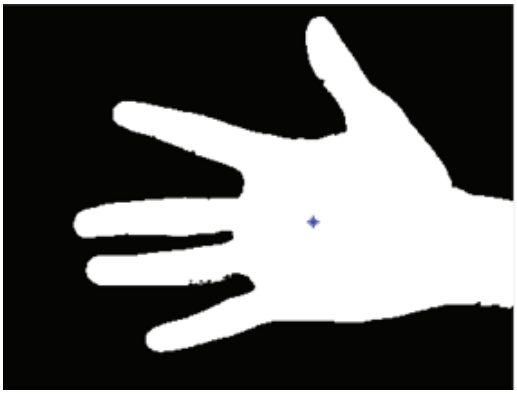

Fig. 2 Binary image

B. Implementation of Region of Interest-Palm Extraction

Region of palm extraction is discussed in this module. The pose corrected range and intensity images are processed to locate regions of interest (ROI) for hand geometry and palm print feature extraction. The first approach based upon landmark points locates a point which is far off the actual center of the palm. It also observed that the approach based upon distance transform may not always locate the same palm center for different images from the same hand with varying poses. However, it still locates a point in the close vicinity of the actual center and such small error is permissible as utilize a set of data points inside the extracted region [9]. Palm print extracted from the range images of the hand offer highly discriminatory features for personal identification. Palm prints are primarily local surface details in the form of depth and curvature of palm lines and wrinkles. It is quite clear that the process of pose normalization has greatly reduced the overlap of genuine and impostor match scores.

Here now employ a much simpler but robust method based upon distance transform to locate the center of the palm. Distance transform computes the Euclidean distance between each foreground pixel (part of the hand) and its nearest pixel on the hand contour (Fig. 3). The point that has the maximum value for the distance transform is considered to be the center of the palm. This is the first approach based upon landmark points locates a point which is far off the actual center of the palm, and also observe that the approach based upon distance transform may not always locate the same palm center for different images from the same hand with varying poses. However, it still locates a point in the close vicinity of the actual center and such small error is permissible as utilize a set of data points inside the extracted region, rather than a single feature point, for further processing.

C. Implementation of Feature Extraction Using Gabor Filter

In this module describes the feature extraction using Gabor filter. Personal authentication based upon 2D palm print has been extensively researched and numerous approaches for feature extraction and matching are available in the literature. Feature extraction techniques based upon Gabor filtering has generally outperformed others. It is a linear filter used for edge detection. Frequency and orientation representations of Gabor filters are similar to those of the human visual system (Fig. 4), and they have been found to be particularly appropriate for texture representation and discrimination. Gabor filters are directly related to Gabor wavelets, since they can be designed for a number of dilations and rotations. However, in general, expansion is not applied for Gabor wavelets, since this requires computation of bi-orthogonal wavelets, which may be very time-consuming.

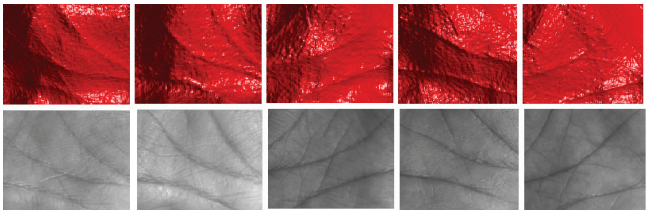

Fig. 3 Samples of 3D and 2D palm prints in the database

Usually, a filter bank consisting of Gabor filters with various scales and rotations is created [9]. The filters are convolved with the signal, resulting in a so-called Gabor space. This approach uses a bank of six Gabor filters oriented in different directions to extract discriminatory information on the orientation of lines and creases on the palm print. Six Gabor filtered images are used to compute the prominent orientation for every pixel in the palm print image and the index of this orientation is binary encoded to forma feature representation. The filter have Gabor function for the specified values of the parameters wavelength, orientation, phase offset, aspect

ratio, and bandwidth will be calculated and displayed as an intensity map image in the output window.

$$G(x, y, u, \sigma) = \frac{1}{2\pi\sigma^2} exp\left\{-\frac{x^2+y^2}{2\sigma^2}\right\} exp\left\{\begin{matrix}2\pi i(uxcos\theta + \\ uysin\theta)\end{matrix}\right\} \quad (1)$$

In this equation, λ represents the wavelength of the sinusoidal factor, θ represents the orientation of the normal to the parallel stripes of a Gabor function, ψ is the phase offset, σ is the sigma of the Gaussian envelope and γ is the spatial aspect ratio, and specifies the elasticity of the support of the Gabor function. Matchers and considerably lower scores for imposter matches. Even if it fails to identify the correct match, a strong matcher will almost always produce significantly high score.

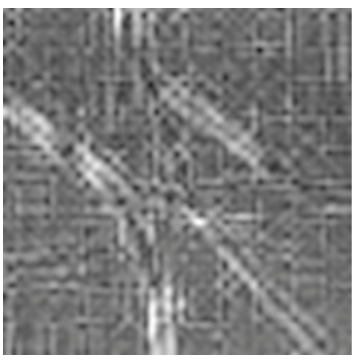

Fig. 4 Texture Extraction

III. 3D Palmprint Feature Extraction

Classify the palm print features into three different levels: shape level, line level and texture level. Shape features are contained in 3D palm print and they are at the coarsest level. Principal line features exist in both 2D and 3D palm print images and they are at the second level, which represent the structural information of palm print principal lines. Texture features are also contained in both 2D and 3D palm print images and they are at the finest level, which represent the detailed features of palm print. Intuitively, the texture information is well suited for palm print discrimination, while the shape and line information can be used for palm print alignment, which is an important step for robust palm print recognition. For 3D ROI, the curvature value is much more stable than the original depth Information [8]. We calculate the mean curvature H of the 3D ROI as follows:

$$H = \frac{\left(1+(h_y)^2\right)h_{xx} - 2h_x h_y h_{xy} + \left(1+(h_y)^2\right)h_{yy}}{2\left(1+(h_x)^2+(h_y)^2\right)^{\frac{3}{2}}} \quad (2)$$

where h is the height of the points in the palm print w.r.t the reference plane, hx, hy, hxx, hyy and hxy are the first, second and hybrid partial derivatives of h.

IV. 2D and 3D Feature Matching

A. Hybrid Fusion Strategy

A general framework of fusion at decision level, which works on ROCs instead of matching scores, is investigated. Under this framework, we further propose a hybrid fusion method, which combines the score-level and decision-level fusions, taking advantage of both fusion modes. The hybrid fusion adaptively tunes itself between the two levels of fusion, and improves the final performance over the original two levels. The proposed hybrid fusion is simple and effective for combining different biometrics. The major drawback of such a fusion framework is that poor quality samples can have adverse influence on the consolidated score since fixed weights are given for all samples. In order to overcome this problem, researchers have come up with fusion approaches that can dynamically weight a match score based upon the quality of the corresponding modality. However, accurately computing the quality of a biometric feature can be very challenging. Therefore, we develop a simple but efficient approach for combining 2D and 3D palmprint scores that are simultaneously extracted from the pose corrected range and intensity images. The proposed Hybrid fusion combination approach attempts to identify and ignore those poor hand geometry match scores using the estimated orientation of the hand.

V. Experimental Results

A) Dataset Description

Since there is no publicly available 3D hand database where hand images are acquired in a contact-free manner, it is developed our own database using a commercially available 3D digital Camera Participants in the data collection process conducted at our institute included mainly students who volunteered to give their biometric data. The database currently contains 118 right hand images (3D and the corresponding 2D) acquired from 120 subjects.

B) Verification Results

In order to ascertain the usefulness of the proposed pose correction and hybrid fusion approaches, to performed verification experiments on the acquired database. In order to evaluate the performance of the proposed system, The Verification experiments on a database of 120 subjects.

The database should include some fake palm prints to test the robustness of the proposed system. However, in this set of experiments, focus on analyzing 2D and 3D palm print features. The main objective was to achieve performance improvement by combining 2D and 3D palm print features that are simultaneously acquired from our imaging setup. For performance criteria, the error measure of a verification system are FAR and FRR as defined in the equations below:

$$FRR = \frac{Number\ of\ rejected\ genuine\ claims}{Total\ number\ of\ genuine\ accesses} 100\%$$

$$FAR = \frac{Number\ of\ accepted\ imposter\ claims}{Total\ number\ of\ imposter\ accesses} 100\%$$

A unique measure, total success rate (TSR) is obtained as follows:

$$TSR = (1 - FAR + FRR | Total\ number\ of\ access) * 100\%$$

Table I Equal Error rate for Combination of 2D and 3D Palm Print Features

Matcher	EER (%)
2D Palm print	1.69
3D Palm print	1.88
(2D+3D) Palm print	0.98
Hybrid Fusion	0.34

VI. Conclusions

In this paper present the experimental results from a newly developed palm print authentication system that can simultaneously acquire and combine 2D and 3D palm print features. This paper also presented the comparative performance evaluation of 2D and 3D palm print representations. Our comparative analysis, where 2D features achieve lower error rates compared to the 3D features, suggests that the 2D features are more discriminative than 3D features for palm print representation. The experimental results show that the 3D palm print technique can not only achieve high recognition rate, but also have high anti counterfeit capability and high robustness to illumination variations and serious scrabbling in the palm surface. In the future, more advanced and powerful feature extraction and matching techniques are to be developed for a better recognition performance.

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