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PATTERN EXTRACTION AND RECOVERING FOR FINGER-VEIN VERIFICATION USING IMAGE ENHANCEMENT

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Abstract: This paper presents a new approach to improve the performance of finger vein identification systems presented in the literature. The proposed system simultaneously acquires the finger vein and low resolution fingerprint images and combines these two evidences using a novel score level combination strategy. We examine the previously proposed finger vein identification approaches and develop a new approach that illustrates it superiority over prior published efforts. The utility of low resolution fingerprint images acquired from a webcam is examined to ascertain the matching performance from such images. We develop and investigate two new score level combinations, i.e.holistic and nonlinear fusion, and comparatively evaluate them with more popular score level fusion approaches to ascertain their effectiveness in proposed system. The rigorous experimental results presented on the database of 6,264 images from 156 subjects illustrate significant improvement in the performance, both from the authentication and recognition experiments.

Index Terms—Hand biometrics, Finger-vein verification, Image enhancement, Representation learning.

I. INTRODUCTION

With our progress toward a global information society, the average person's life has become threatened by heinous occurrences that can originate anywhere in the world. As a result, there is an intense need for personal authentication systems that can prevent spoofing and other criminal impersonation in such areas as financial (cash or credit card) withdrawals, passport and driver's license identification, entry into important facilities, apartment complexes or offices, access to IT equipment, and a broad range of other applications [18]. Biometrics systems have become the ideal answer to these security needs and are already being adopted worldwide. Biometrics deals with identification of individuals based on their biological and/or behavioral features. These features include fingerprint, finger-vein, face, iris, voice, palm print, DNA, retina, signature, keystroke etc. Out of these, fingerprint techniques are widely used in authentication systems. Finger print and Finger Vein are growing and popular biometric identification and authentication technologies. They are used in large no. of commercial applications and applications of identity management. They are also used by forensic experts in criminal investigations. Finger Print and Finger Vein identification is based on its uniqueness and persistence. The uniqueness of the fingerprints and veins is accepted over the time. The pattern of the friction ridges on each finger of an individual is unique. Even twins can be differentiated based on the finger prints. The pattern on the fingers is immutable. The finger surface injuries such as cut

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damage the finger pattern only temporarily but the original structure reappears after the injury heals i.e. the basic characteristics of fingerprints are persistent. Finger-veins are internal characteristics of the finger. It is non-contacting and hidden structure. Finger-veins are visible only under Infrared light so it provides higher level of security as can't be stolen without the knowledge of an individual. A lot of research has been done on the fingerprint and finger-veins in biometrics. An automated finger image matching framework which can reliably extract the finger vein and texture shape features and achieve much higher accuracy than previously proposed finger vein identification approaches is presented in [1]. A system for fingerprint privacy protection by combining two fingerprints into a new identity is introduced in [2]. This system has the advantage in creating virtual identity. Alessandra A. Paulino et al [3] proposed a fingerprint matching algorithm designed for matching latents to rolled/plain fingerprints which is based on a descriptor-based Hough Transform alignment which shows superior performance. Jinfeng Yang et al [13] proposed a new finger-vein image restoration method to improve the quality of finger-vein images. In this paper, we propose a novel personal authentication system which uses simultaneously acquired finger vein and finger texture images of the same person. These two images are combined into a virtual fingerprint. The feature extracted templates of the virtual fingerprints are stored in the database for the authentication which requires two query fingerprints, finger vein and finger texture. The mixing of finger vein and fingerprint has benefits in terms of storage and security. It can be used to generate large set of virtual identities. Even if this dataset is stolen it is highly impossible to separate these two images thus it is highly secure [19].

II. THE PROPOSED SYSTEM FOR PERSONAL AUTHENTICATION

Fig. 1 shows the block diagram [1] for proposed personal authentication system.

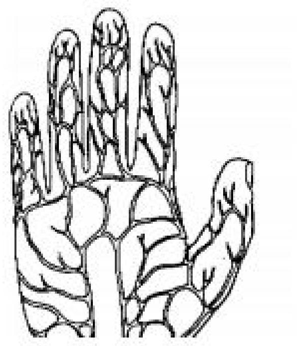

Fig. 1: Vein pattern in the finger and palm skin

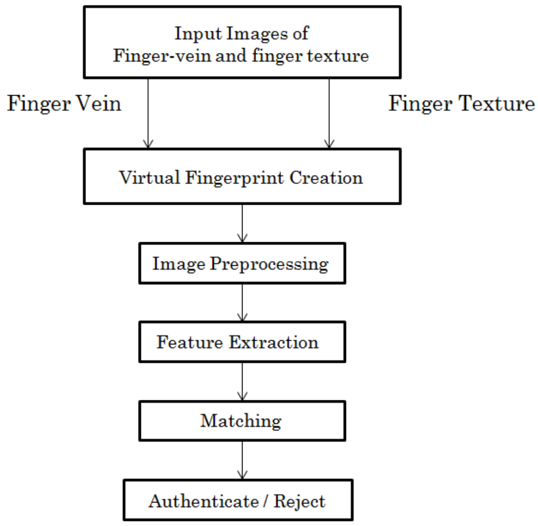

Fig.2. Block Diagram for the proposed personal identification using finger-vein and finger texture combination

As the finger texture images are captured using low resolution webcam, they are of low quality. These images do not contain minutiae or level-2 features. The acquired finger images are noisy. Therefore these images are subjected to pre-processing

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steps. The pre-processing steps include image normalization, segmentation and enhancement.Our approach aims, first, at segmenting foreground (vein) pixels from background pixels by predicting the probability of a pixel to belong to a vein pattern given limited knowledge, and, second, at recovering missing vein patterns. Compared to current state of the art segmentation and recovering approaches, that are based on image processing techniques, our approach does not segment or recover an image based only on its pixels and their correlations, but it does so by relying also on rich statistics on nonlinear pixels correlations, through a hierarchical feature representation learned by a deep neural network from a large training set. This is a major advantage over traditional approaches as relying only on noisy input images for segmentation or vein recovery may lead to severe errors. The main paper contributions are summarized as follows: 1) We propose an automatic scheme to label pixels in vein regions and background regions, given very limited human knowledge. We employ several existing baselines approaches to extract (segment) the vein network from an image and use their combined output automatically to assign a label for each pixel. Such a scheme avoids the heavy manual labeling and may also reduce label errors, especially for ambiguous pixels.

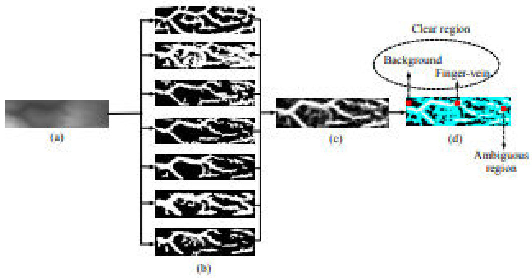

Fig. 3: Labeling the vein and background pixels: (a) Original image; (b) Extracted vein features (patterns) from various approaches; (c) Probability map from (c); and (d) pixels with label (clear region) and pixels without label (ambiguous region, in cyan).

1.1 Motivation and Related Work

The blood vessels, as part of circulatory system, transport blood throughout the body to sustain the metabolism, using a network of arteries, veins and capillaries. The usage of such vascular structures in the palm, palm-dorsal and fingers has been investigated in the biometrics literature [2]-[9], [33]-[35] with high success. The finger vein patterns are believed to be quite unique, even in case of identical twins and even between the different fingers an individual. There are two key factors that are cited for the preference of finger vein biometrics; firstly, the finger veins are hidden structures, it is extremely difficult to steal the finger vein patterns of an individual without their knowledge and therefore offering high degree of privacy. Secondly, the usage of finger vein biometrics offers strong anti-spoofing capabilities as it can also ensure liveness in the presented fingers during the imaging. Personal identification using finger vein patterns has invited lot of research interest [1]and currently several commercial products are available for civilian applications. The biometrics identification

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from finger vein patterns using normalized cross correlation of finger vein images is detailed in. Miura *et al.* [5] have further improved the performance for the vein identification using repeated line tracking algorithm. The robustness in the extraction of finger vein patterns can be significantly improved with the usage of local maximum curvature across the vein images and is detailed in reference [6] with promising results. Wu and Ye [3] have successfully investigated finger vein identification using Radon transform based statistical features and probabilistic neural network classifier. However the database employed in this work is too small to generate reliable conclusion on the stability of such features in the noisy vein patterns. The curvelet based extraction of finger vein patterns and its classification using backpropagation neural network is described in [4]. The performance from this approach is shown to be very high but the key details of their implementation are missing in the paper. Lee and Park [2] have recently investigated the restoration of finger vein images using point spread function. Authors suggest significant improvement in the performance for the vein identification using such restored finger images. The finger vein imaging setup illustrated in [2]-[4], is rather constrained and restricts the rotation or the movement of fingers during the imaging. A survey of prior work on finger vein identification suggest that although researchers have illustrated highly promising results, this area lacks systematic study, comparative evaluation of performance from (would be promising) previously proposed approaches and importantly there is no publicly available finger vein database that researchers can utilize for performance comparison and benchmarking.Human hands are easier to present, convenient to be imaged, and can reveal variety of features that can be observed with variety of illuminations (visible, near infra red, thermal infrared) and in wide range of imaging resolutions. In addition to fingerprints features, the palmprint, finger knuckle and hand geometry [1] acquired in visible illumination, palm-vein features acquired from near infrared and far infrared imaging, has invited lot of attention from researchers and developers over the last decade.Recently the usage of low-resolution face images using mobile phones and video have been explored with promising results. The conventional fingerprint identification is generally achieved with high resolution (over 400 dpi) imaging and offers strong identification capabilities. The usage of low-resolution finger images (less than 75 dpi), that can be acquired from traditional *webcam* installed in laptops and mobile phones, also deserves more rigorous efforts to ascertain its utility in human identification for civilian and forensic applications.

1.2 Our Work

The individuality of fingerprints can be largely attributed to the anomalies in the friction ridges (*e.g.* ridge endings, bifurcations, *etc.*) which can be acquired when the imaging resolution is higher than 400 dpi. The low resolution finger images that can be typically acquired from the webcam imaging often illustrate finger flexion creases and also the friction ridges which are rather blurred, *i.e.*, inadequate to clearly extract the ridge endings and bifurcations. Despite poor image clarity (or stability), such finger surface texture features can be jointly acquired and exploited for personal identification as

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investigated in this paper. The generic vascular network is highly unique in human fingers and varies from thick to thin. However, the quality of finger vein images can vary across the user population, depending upon the physiological composition, gender, medical conditions, *e.g.* anemia, hypotension, hypothermia, *etc*. The quality of finger vein images can be highly influenced by the imaging conditions; vein patterns can be distorted from the finger pressure in conventional setup [2]-[4], while unconstrained imaging, attempted in this paper, can introduce high intra class variations. Therefore it is judicious to simultaneously acquire the finger vein and finger surface images for more reliable personal identification.

A. Generation of Virtual Fingerprint

The input finger vein and finger texture images are added to generate a virtual identity. This virtual fingerprint is then subjected to preprocessing steps for further processing.

B. Image Preprocessing

1) *Image Normalization*: In this, the image is subjected to binarization with global threshold value. The isolated and loosely connected regions in the binarized are eliminated by applying Canny Edge Detector to the image and subtracting the resulting edge map from the binarized image.

2) *Image Segmentation:* The obtained binary mask in image normalization is used to segment the ROI (Region of Interest) from the original finger-vein image. The orientation of the finger-vein image is determined from the orientation of the binary mask. The normalized 2nd order moments [1] are calculated as follows:

$$\alpha_{12} = \frac{\sum_{(x,y)\epsilon R}\left(y - g_y\right)(x - g_x)I(x,y)}{\sum_{(x,y)\epsilon R} I(x,y)}$$

$$\alpha_{11} = \frac{\sum_{(x,y)\epsilon R}(y - g_y)^2 I(x,y)}{\sum_{(x,y)\epsilon R} I(x,y)}$$

$$\alpha_{22} = \frac{\sum_{(x,y)\epsilon R}(x - g_x)^2 I(x,y)}{\sum_{(x,y)\epsilon R} I(x,y)}$$

Where I = Image (gx,gy) = Position of centroid in the image The orientation of the image is estimated as given below:

$$\omega = \begin{cases} \tan^{-1}\left\{\dfrac{\alpha_{11} - \alpha_{22} + \sqrt{(\alpha_{11} - \alpha_{22})^2 + 4\alpha_{12}^2}}{-2\alpha_{12}}\right., \alpha_{11} > \alpha_{22} \\ \tan^{-1}\left\{\dfrac{-2\alpha_{12}}{\alpha_{22} - \alpha_{11} + \sqrt{(\alpha_{22} - \alpha_{11})^2 + 4\alpha_{12}^2}}\right., \alpha_{11} \le \alpha_{22} \end{cases}$$

This orientation is used for rotational alignment of the ROI of finger-vein image.

3) *Image Enhancement:* The ROI image is subjected to local histogram equalization. Histogram equalization is used to enhance the image and to improve the contrast and the details in the ROI of original image.

C. Feature Extraction

Gabor filter is used for image feature extraction. Gabor filters are known to achieve the maximum possible joint resolution in spatial and spatial-frequency domain. Gabor filters capture both local orientation and frequency information from a finger image. By tuning a Gabor filter to specific frequency and direction, the local frequency and orientation information can be obtained.

The Gabor with specified orientations are created and then convolved with the enhanced image to remove the unwanted regions. The analytical form of 2-D Gabor filter [1] is given by

$$h(x,y,\theta,f,\sigma_x,\sigma_y) = e^{\left[-\frac{1}{2}\left(\frac{x_\theta^2}{\sigma_x^2}+\frac{y_\theta^2}{\sigma_y^2}\right)\right]} \times e^{2\pi f x_\theta}$$

Where $x\theta$=$x\cos\theta$+$y\sin\theta$ $y\theta$= $-x\sin\theta$ +$y\cos\theta$ f = Frequency of the sin wave θ = Orientation of Gabor filter σx = Standard deviations of the Gaussian envelope along

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the x axis σy = Standard deviations of the Gaussian envelope along the y axis. The feature extracted image is subjected to morphological operations to enhance the patterns. The morphological top-hat operation is applied to the image. It performs morphological top-hat filtering on the grayscale or binary image. Top-hat filtering computes the morphological opening of the image and then subtracts the results from the input image. This corrects the uneven illumination when the background is dark. This is represented as [1] follow:

$$z(x,y) = f(x,y) - \left(f(x,y) \ominus b\right) \circledast b$$

Where = Gray-scale erosion = Gray-scale dilation b = Square structuring element The result of the morphological operation is encoded follows:

$$R(x,y) = \begin{cases} 255, & z(x,y) > 0 \\ 0, & z(x,y) \le 0 \end{cases}$$

D. Matching

The features extracted from the virtual fingerprint are already stored in a database. The features of the combined image are matched with all the images in the database to check whether the input images are matched with any one of the images in the database.

The SURF detector-descriptor scheme is used for matching two feature vector templates. This detector uses the determinant of Hessian Matrix because of its good performance in computation time and accuracy. The Hessian Matrix, H, is the matrix of partial derivatives of the function f given by $H \quad F \quad x{,}y$ = $\partial 2f\partial x2\partial 2f\partial x\partial y\partial 2f\partial x\partial y\partial 2f\partial y2$ The determinant of this matrix, known as the discriminant, is calculated by, det H = $\partial 2f\partial x2\partial 2f\partial y2-\ (\partial 2f\partial x\partial y)2$ The value of this discriminant is used to detect the interest points. Once the interest points in both, the input feature vector and the database feature vector are detected, the Sum of Squared Differences, SSD, is used for matching. If the resulting matching score is greater than the threshold then the input images and the person is authenticated.

III. EXPERIMENTAL RESULTS AND DISCUSSION

A. Database

The database used is The Hong Kong Polytechnic University Finger Image Database (Version 1.0). It consists of 6,264 images from 156 subjects. The finger texture images are captured using webcam having resolution of 75 dpi and the finger-vein images are captured using an infra-red camera and Light Emitting Diode [1].

B. Performance Evaluation

All codes are written in MATLAB. In this paper, we worked on 100 images of finger vein and finger texture each from the provided finger database. The feature extracted images of the virtual fingerprints are already stored in an enrollment database. The matching accuracy of the system is compared with the existing approaches. Fig. 3 shows the results of Virtual Finger pre-processing and feature extraction. The last image in Fig. 3 shows the point matches of test and database image on the graph. The results show that the pre-processing performed on the vein and texture images has been effective in extracting the features. Gabor filters have both frequency and orientation selective properties so it extracts the features efficiently. According to the work presented in [1], if the finger texture image is not matched due to its low quality then even if the finger vein image is matched the genuine person is rejected. We provide

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a solution to this by combining the vein and texture images. Our system provides matching accuracy of 96 %.

In terms of memory required and execution time, our system has improved performance than the system presented in [1]. Unlike in [1], we are storing feature extracted images of the virtual fingerprint only. So the database space required is reduced to 50% as we are generating the virtual fingerprint from finger vein and finger texture. The approach in [1] performs preprocessing and feature extraction on both finger vein and finger texture separately. In our system, only the virtual fingerprint is subjected to preprocessing and feature extraction so the execution time or the time required for the verification of a person is reduced to almost 50%.

C. Comparison with Previous Methods

The experimental results in table 1 illustrates that our approach performs significantly better than the existing approaches in [1] and [3] in terms of matching accuracy.

TABLE I PERFORMANCE EVALUATION IN TERMS OF MATCHING ACCURACY

Approach	Matching Accuracy (%)
Our method	**92**
Gabor Filter for score fusion of finger vein and finger texture [1]	90
Matched Filter [1]	86
Repeated Line Tracking [1]	77
Maximum Curvature [1]	73
Hough Transform [3]	75

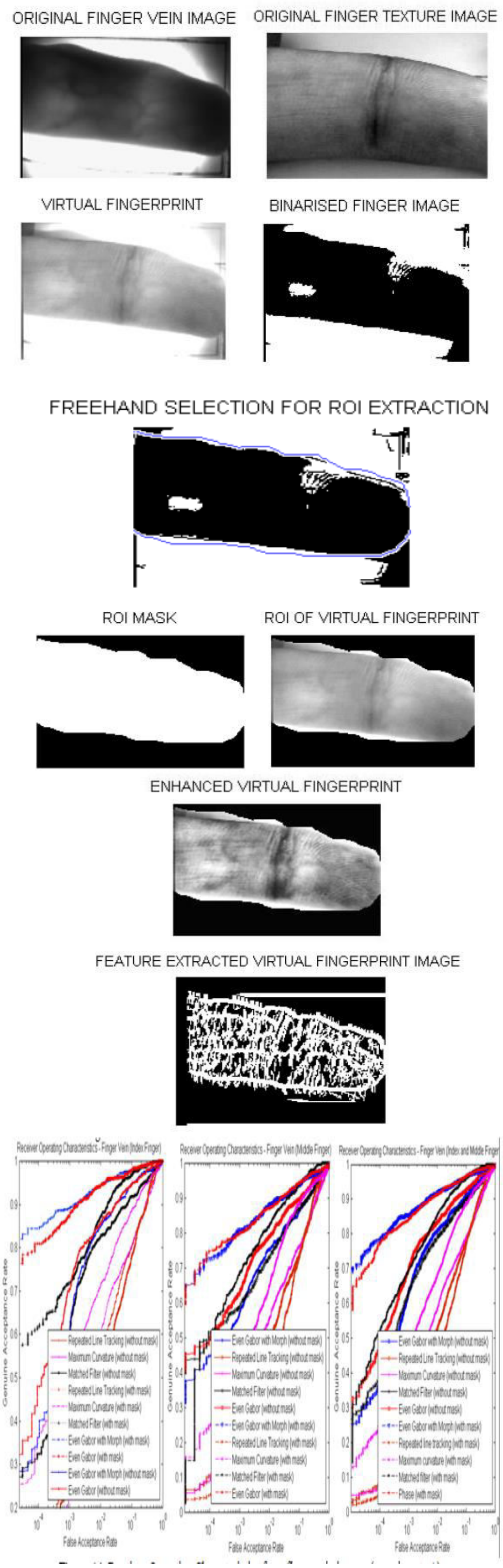

Fig. 4 Results of Virtual Finger pre-processing and feature extraction

IV. CONCLUSIONS

In this paper, we have discussed and implemented the personal authentication framework by using simultaneously acquired finger texture and vein images. We generated virtual fingerprint combining finger vein and finger texture image and used Gabor filter for feature extraction. The experimental results show that our system provides improves matching accuracy of 92%. The processing time for the verification of the person is approximately 20 to 25 seconds for the database of 100 persons. This is significantly lower than the existing approach in [1]. The memory requirement of our system is also reduced to 50% compared to the system in [1].

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