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To Identify of Human Using Finger-Vein Imaging

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Abstract - Biometric system has been actively emerging in various industries and continuing to roll to provide higher security features for access control system. The proposed system simultaneously acquires the finger surface and subsurface features from finger-vein and finger print images. This paper reviews the acquired finger vein and finger texture images are first subjected to pre-processing steps, which extract the region-of-interest (ROI). The enhanced and normalized ROI images employed to extract features and generate matching score. For this I will develop and investigate two new score-level combinations i.e. Gabour filter, Repeated line Tracking and Neural network comparatively evaluate them more popular score-level fusion approaches to ascertain their effectiveness in the proposed system. MATLAB software will be using for proposed work.

Keywords - *Finger-Vein Recognition, Gabour Filter, Repeated Line Tracking, Neural Network.*

1. Introduction

Biometrics is the technique of science which is used to identifying a person using one's physiological or behavioral characteristics. The physiological traits include physical features i.e. iris, face, hand geometry, finger print or vein, palm print, retina, etc, and behavioral traits include behavior features i.e. gait, voice, signature, etc. The basic purpose of biometrics is to provide security. The tremendous growth in the demand for more user friendly and secured biometrics systems has motivated researchers to explore new biometrics features and traits [1]. The anatomy of human fingers is quite complicated and largely responsible for the individuality of fingerprint and finger veins.

Due to more uniqueness of fingerprint, it has been attributed to the random imperfections in the minutiae or level-2 fingerprint features. The acquisition of minutiae features needs imaging resolution higher than 400 dpi [1]. The conventional level-1 fingerprint features, which show all finger details such as ridge flow and pattern type [8], can be extracted from the low-resolution fingerprint images [2]. Such features are useful for fingerprint classification and commercially available for fingerprint identification systems that utilize such level-1 features. The use of such features, which can be more conveniently be acquired from the low-resolution images or at a distance, deserves attention for its possible use in personal identification for civilian and/or forensic applications[1]. The images at such low resolution typically illustrate friction creases and also friction ridges but with varying clarity. Several biometrics technologies are susceptible to spoof attacks in which fake fingerprint, static palm prints, and static face images can be successfully employed as biometric samples to impersonate the identification. Therefore, several livens counter measures to detect such sensor-level spoof attacks have been proposed, e.g., fingers response to electrical impulse, finger temperature and electrocardiographic signals , time-varying perspiration patterns from fingertips, and a percentage of oxygen saturated hemoglobin in the blood[9]. Despite the variety of these suggestions, only a few have been found suitable for online fingerprint identification.

These techniques require close contact between using sensors with the fingers, which makes this technique unsuitable for unconstrained finger images or when the presented fingers are not in close proximity with the sensors. The acquired finger-vein and finger texture images are first subjected to preprocessing steps, which automatically extract the region-of-interest images while minimizing the translational and rotational variations. After normalized, ROI extracted and enhanced images are employed to extract features and then generate matching scores similar with a conventional biometrics system. The combined matching scores are used to authenticate the user from finger image.

2. Finger Vein Identification

The acquired finger images are noisy with rotational and translational variations resulting from unconstrained or denoise imaging. Therefore, the preprocessing steps to be performed at input an image that includes:

1) Segmentation of ROI,
2) Translation and orientation alignment,
3) Image enhancement to extract the features of finger image.

2.1 Image Normalization

The basic purpose of Normalization is to change the range of pixel intensity value. Sobel edge detector is used to the image to the remove background portions connected to it. Eliminating number of the connected white pixels being less value than a threshold value [1].The resulting binary mask is formed. Binarization is a method of transforming grayscale image pixels into either black or white pixels by selecting a threshold.

2.2 ROI Extractor

In the finger images, there are many unwanted regions has been removed by choosing the interested area in that image. ROI is said to be “Region of Interest” which is a useful area. Then obtain binary mask and used to segment the ROI from the original finger-vein image. The orientation of the image is determined to remove the low quality images that present in finger vein image [6]. The blood vessels, as part of the circulatory system, transport blood throughout the body to sustain the metabolism, using a network of arteries, veins, and capillaries. The use of such vascular structures in the palm, palm–dorsal, and fingers has been investigated in the biometrics literature with high success. The finger-vein patterns are believed to be quite unique, even in the case of identical twins and even between the different fingers of an individual. There are two key factors that are cited for the preference of finger-vein biometrics. First, the finger veins are hidden structures; it is extremely difficult to steal the finger-vein patterns of an individual without their knowledge, therefore offering a high degree of privacy. Second, the use of finger-vein biometrics offers strong antispoofing 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]–[9], and currently, several commercial products have been available for civilian applications. The biometrics identification from finger-vein patterns using normalized cross correlation of finger-vein images is detailed in [7]. Miura et al. [5] have further improved the performance for the vein identification using a repeated line tracking algorithm. The robustness in the extraction of finger-vein patterns can be significantly improved with the use of local maximum curvature across the vein images and is detailed in [6] with promising results. Wu and Ye [3] have successfully investigated finger-vein identification using Radon-transform-based statistical features and a probabilistic neural network classifier. However, the database employed in this paper is too small to generate a 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 a back-propagation neural network are described in [4]. The performance from this approach is shown to be very high, but the key details of their implementation are missing in this paper. Lee and Park [2] have recently investigated the restoration of finger-vein images using a point spread function. The 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] and 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 a systematic study, i.e., a 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 a variety of features that can be observed with a variety of illuminations (e.g., visible, near infrared, or thermal infrared) and in a wide range of imaging resolutions. In addition to fingerprint features, the palmprint finger knuckle [15] and hand geometry [1] acquired in visible illumination, and palm-vein features acquired from near-infrared and far-infrared imaging have invited lot of attention from researchers and developers over the last decade.

Recently, the use 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 use of low-resolution finger images (less than 75 dpi), which can be acquired from a 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.

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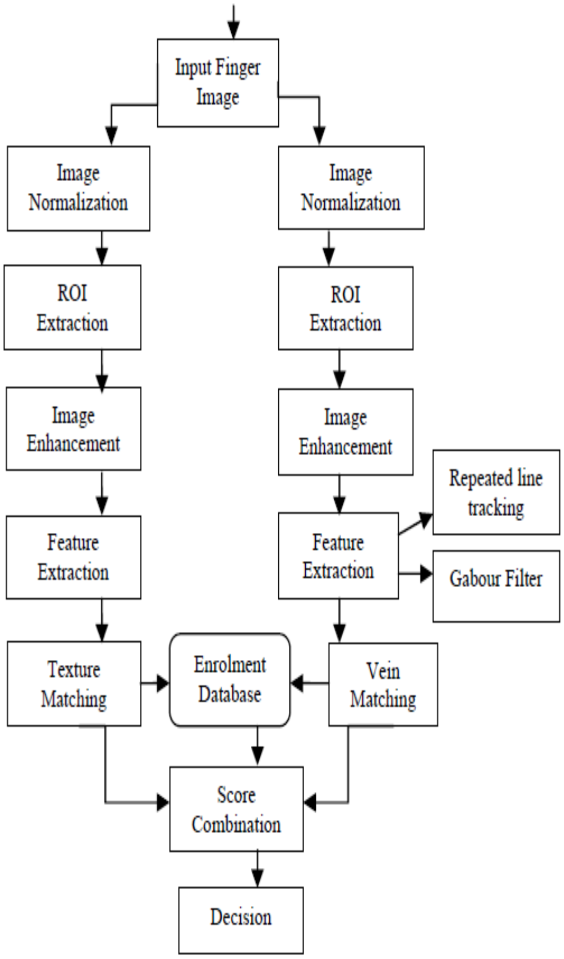

Fig. Procedure for identification of human using finger-vein imaging.

2.3 Image Enhancement

The acquired image is thin and not clear. This can be attributed to create the uneven illumination. The acquired images are first divided into 30 × 30 pixels sub blocks and compute the average gray level of the each block. This average gray level is then used to construct average background image using bi-cubic interpolation. The segmented finger-vein images use automatically filled background area that does not have any useful details. Then, images divided into sub blocks results in the biased estimation of background illumination [2]. The resulting image is then subjected to the local histogram equalization to obtain the final enhanced vein image.

2.4 Feature Extraction

The normalized and enhanced finger-vein images from the imaging setup depict a vascular network with changing some thickness, clarity, and ambiguity on the topological imperfections/connections [3]. We will use the Repeated Line Tracking and Gabor filter for feature extraction.

1) The Repeated Line Tracking: The repeated line tracking method gives a promising result in finger vein identification: The idea is to trace the veins in the image by chosen directions according to predefined probability in the horizontal and vertical orientations. After this starting seed will randomly selected and the whole process will repeatedly done for a certain number of times.

2) Gabour Filter: It is a linear filter and used for edge detection. The representation of frequency and orientation Gabour filter is similar to those of human visual system. It has been found to be particularly appropriate for texture representation and discrimination. Gabour filter is directly related to Gabor wavelet and can be designed for number of dilations and rotations. Gabour filter can be viewed as a sinusoidal plane of particular frequency and orientation modulated by a Gaussian envelope.

3. Finger Texture Image

3.1 Normalization

In texture preprocessing, Sobel edge detector is used to obtain the edge map and localize the finger boundaries. This edge map is isolated with noise and it can be removed from the area threshold. We extract a fixed 400 × 160 pixel area, at a distance of 85 × 50 pixels, respectively, from the lower and right boundaries, from this rectangular region [6]. This 400 × 160 pixel image is then used as the finger texture image for the identification.

3.2 ROI Extractor

In the finger texture images, there are many unwanted regions has been removed by choosing the interested area in that image. The useful area is said to be "Region of Interest" (ROI) [6]. Finger texture image is subjected to median filtering to eliminate the impulsive noise. Therefore obtain the background illumination image from the average of pixels in 10×10 pixel image sub blocks and bi-cubic interpolation [2]. The resulting image is subtracted from the median filtered finger texture image and then subjected to histogram equalization.

3.3 Finger Texture Image Feature Extraction

The Localized Random Transform (LRT) and Gabor filter is used for finger texture image feature extraction. The Radon transform [17] is very efficient in detecting and locating lines in the image by integrating the intensity of the image in all possible/predefined orientations. The LRT is efficient in extracting line and curve segments in the local area. Gabor filters optimally capture both local orientation and frequency information from a fingerprint image.

3.4 Texture Matching

In texture matching, the finger texture image features extracted are encoded in orientations. The matching score attempts to compute the best matching scores between two images while accounting for such possible spatial shifts and rotation. The blockwise matching scheme is used for texture matching.

4. Score Combination

Score combination predicts that the vein and texture image is matched with the database. The database contains the feature of all vein and texture images. The Extract features and Match features are use. The experimental results presented in this section are focused to ascertain the performance improvement that can be achieved from the simultaneous acquisition of finger-vein and finger texture images. The neural network will used to improve the performance of system. Fig 1 shows the distribution of finger-vein and finger texture matching scores from the genuine and imposter matches.

5. Conclusion

This paper will present a complete finger image-matching framework by simultaneously utilizing the finger vein and finger texture features. It will present a new technique for the finger-vein identification that extract the features of finger image and obtain higher accuracy than previously proposed finger-vein identification approaches. Our authentification scheme will work more effectively in more realistic scenarios and leads to a more accurate performance, as will be demonstrated from the experimental results. We will examine a complete automated approach for the authentification of person by using finger surface texture images for the performance improvement.

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