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Palm-Vein Image Recognition of Human Using Discrete Enhancement

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ABSTRACT

This project presents new approach to develop the appearance of palm vein verification that uses blood vessel patterns as a personal identifying factor. The proposed approach of the vein is hard for replacement, since veins are internal to the human body and the palm vein authentication technology offers a high level of accuracy. The palm-vein-based approach attempts to be more effectively accommodating the potential deformations, revolving and translational changes by encoding the orientation preserving features. An Image Analysis the technique for Vascular Pattern of Hand Palm, which in turn leads towards the Palm Vein Authentication of an individual. Near-Infrared Image a Palm Vein pattern is taken and passed through four different processes or algorithms to process the Infrared Image in such a way that the future authentication can be done accurately or almost exactly. These four different processes are: 1) Junction point algorithm. 2) Hand Geometry algorithm 3) Pose invariant algorithm 4) Calculation of Rank Matrix. The resultant Images will be stored in a Database, as the vascular patterns are unique to each individual, so future authentication can be done by comparing the pattern of veins in the palm of a person being authenticated with a pattern stored in a database.

KEY WORDS: Palm-Vein Recognition, Vascular Patterns, Authentication Junction Point Algorithm, Hand Geometry algorithm, Pose invariant algorithm, Calculation of Rank Matrix .

I. INTRODUCTION

AUTOMATED human identification is one of the most critical and challenging tasks to meet growing demand for stringent security. The usage of physiological and/or behavioral characteristics of humans, i.e., biometrics, has been extensively employed in the identification of criminals and matured as an essential tool for law enforcement departments. The biometrics- based automated human identification is now highly popular in a wide range of civilian applications and has a become powerful alternative to traditional (password or token) identification systems. Human palms are easier to present for imaging and can reveal a variety of information. Therefore, palm-print research has invited a lot of attention for civilian and forensic usage . However, like some of the popular biometrics (e.g., fingerprint, iris, face), the palm-print biometric is also prone to sensor level spoof attacks. Remote imaging using a high-resolution camera can be employed to reveal important palm-print details for possible spoof attacks and impersonation. Therefore, extrinsic biometric features are expected to be more vulnerable for spoofing with moderate efforts. Novel approach for hand matching that is better even in the presence of large hand pose variations. To involve determination of hand’s orientation in 3-D space followed by pose normalization. Multimodal palm vein and hand geometry features, which are extracted from the user’s pose normalized textured 3-D hand, are used for matching. A hand identification approach based upon extracting distinctive features that are invariant to projective transformations.

II. PREPROCESSING

The palm-vein images in contact-less imaging present a lot of translational and rotational variations. Therefore, more stringent pre-processing steps are required to extract a stable and aligned ROI. The pre-processing steps essentially recover a fixed-size ROI from the acquired images which have been normalized to minimize the rotational, translational, and scale changes. This is followed by the nonlinear enhancement so that the vein patterns from ROI images can be observed more clearly. Since the intensity function of a digital image is only known at discrete points, derivatives of this function cannot be defined unless we assume that there is an underlying continuous intensity function which has been sampled at the image points. With some additional assumptions, the derivative of the continuous intensity function can be computed as a function on the sampled intensity function, i.e., the digital image. It turns out that the derivatives at any particular point are functions of the intensity values at virtually all image points. However, approximations of these derivative functions can be defined at lesser or larger degrees of accuracy. Median filtering is a nonlinear process useful in reducing impulsive, or salt-and-pepper noise. It is also useful in preserving edges in an image while reducing random noise. The morphological operations are dilation and erosion. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries. The number of pixels added or removed from the objects in an image depends on the size and shape of the structuring element used to process the image. In the morphological dilation and erosion operations, the state of any given pixel in the output image is determined by applying a rule to the corresponding pixel and its neighbors in the input image. The rule used to process the pixels defines the operation as a dilation or an erosion. The key objective while segmenting the ROI is to automatically normalize the region in such a way that the image variations, caused by the interaction of the user with the imaging device, can be minimized. In order to make the identification process more effective and efficient, it is necessary to construct a coordinate system that is invariant/robust (or nearly) to such variations. It is judicious to associate the coordinate system with the palm itself since we are seeking the invariance corresponding to it. Therefore, two webs are utilized as the reference points/line to build up the coordinate system, i.e., the web between the index finger and middle finger together with the web between the ring finger and little finger. These web points are easily identified in touch-based imaging (using pegs) but should be automatically generated for contact-less imaging. The acquired palm images are first binarized, so that we are able to separate the palm region from the background region. This is followed by the estimation of the distance from center position of the binarized palm to the boundary of palm. We locate the two webs by finding the corresponding local minima from the calculated distance. Fig 2 shows the block diagram for personal identification using palm –vein images. The potential scale changes in the contact-less environment can be quite large, and in order to account for this variation, it is wise to adaptively select the location and size of the ROI according to certain image-specific measures from the palm.

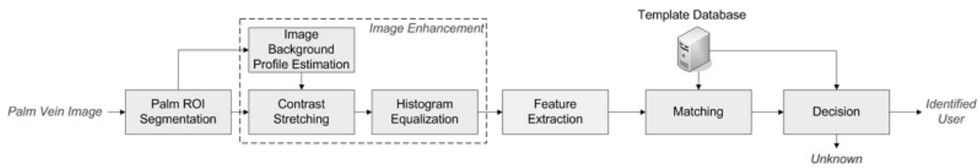
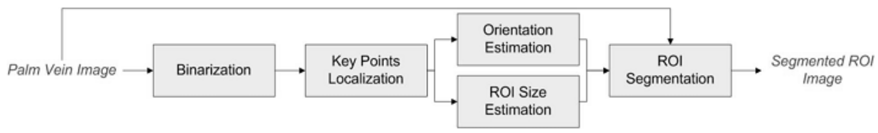


Fig. 2. Block diagram for personal identification using palm-vein images.



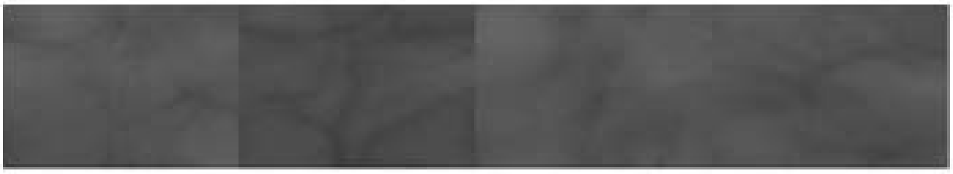
III IMAGE ENHANCEMENT

Image enhancement techniques help in improving the visibility of any portion or feature of the image supressing the information in other portions or features. Enhancement is the modification of an image to alter impact on the viewer. Generally enhancement distorts the original digital values; therefore enhancement is not done until the restoration processes are completed.

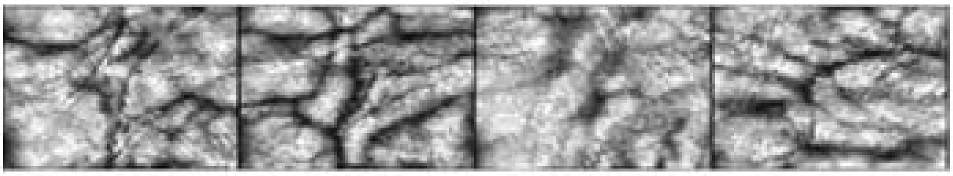
NEAR-INFRARED ILLUMINATION

The palm-vein images employed in our work were acquired under Near-Infrared Illumination (NIR); the images generally appear darker with low contrast. Therefore, image enhancement to more clearly illustrate the vein and texture patterns is required. We first estimate the background intensity profiles by dividing the image into slightly overlapping 32 blocks (three pixels overlapping between two blocks to address the blocky effect), and the average gray-level pixels in each block are computed. Subsequently, the estimated background intensity profile is re-sized to the same size as the original image using bi-cubic interpolation and the resulting image is subtracted from the original ROI image.

Finally, histogram equalization is employed to obtain the normalized and enhanced palm-vein image. As can be observed from Fig. 3.1, the enhancement has been quite successful in improving the details and contrast of the ROI images.



(a)



(b)

Fig 3.1 : Illustration of image enhancement: (a) original ROI images, (b) correspondingly enhanced ROI images of (a).

CANNY EDGE DETECTION

The Canny edge detector is an edge detection operator that uses a multi-stage algorithm to detect a wide range of edges in images. It Canny also produced a computational theory of edge detection explaining why the technique works. In this situation, an "optimal" edge detector means:

- Good detection – the algorithm should mark as many real edges in the image as possible.
- Good localization – edges marked should be as close as possible to the edge in the real image.
- Minimal response – a given edge in the image should only be marked once, and where possible, image noise should not create false edges.

To satisfy these requirements Canny used the calculus of variations – a technique which finds the function which optimizes a given functional. The optimal function in Canny's detector is described by the sum of four exponential terms, but can be approximated by the first derivative of a Gaussian. This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values. A Gaussian blur (also known as Gaussian smoothing) is the result of blurring an image by a Gaussian function. It is a widely used effect in graphics software, typically to reduce image noise and reduce detail. The visual effect of this blurring technique is a smooth blur resembling that of viewing the image through a translucent screen, distinctly different from the bokeh effect produced by an out-of-focus lens or the shadow of an object under usual illumination. Gaussian smoothing is also used as a pre-processing stage in computer vision algorithms in order to enhance image structures at different scales.

IV. FEATURE EXTRACTION

The normalized and enhanced palm-vein images depict curved vascular network/patterns, and these vessels can be approximated by small line segments which are rather curved. Therefore, in this project, we propose to use two new approaches to extract such line-like palm-vein features. In addition, a neighborhood matching scheme that can effectively account for more frequent rotational, translational variations, and also to some image deformations in the acquired image.

In order to ascertain the effectiveness and robustness of the proposed approach for the palm-vein identification, we performed rigorous experiments on both contact-less and contact- based database systematically evaluated and compared all these methods together with our proposed ones, so that we can get more insights into the problem of palm-vein identification.

The software of the Performance Analysis on Palm-Vein based Authentication for security Applications values is classified into 2 modules.

1. Juncture Point Algorithm
2. Hand Geometry

The database contains a set of hand vein images. A single hand vein image is given as input by mentioning the file name in the GUI. If the input image is present in the database then corresponding information is displayed. Else an error message is displayed. In-order to compare the input image and the images in the database the following four modules should be implemented. Initially the input image is binarized and converted into a matrix form.

MODULE 1 :(Junction Point Algorithm)

Three vein intersecting points are considered. The coordinates of such three points are noted and the distance between the three points are noted. Fig 4.1 shows junction point in plam vein.These three points and the distances, of the input image are compared for the images in the database. Centroid for the three points are also noted and compared with the image in the database.

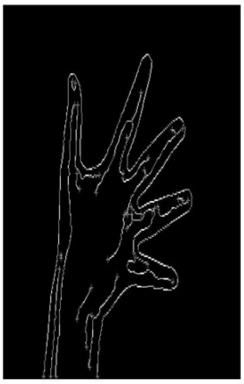


Fig 4.1 Junction points in palm veins

Line detection

We detected the lines and orientation on the image using edge finder .Morphological operation is used to remove isolated edge points. An edge link process is developed to least square fit the detected edges to a set of line segments. An example of the line detection of the region-of-interest (ROI) is shown. The ROI is the centre part of the palm vein images. It is extracted based on the two webs of the hand image.

In computer vision, a junction is defined as the point where two or more contours meet. The junctions can be used as salient features for object classification algorithms or to improve edge detection. Current junction analysis methods include convolution, which applies a mask over a sub-region of the image, and diffusion, which propagates gradient information from point-to-point based on a set of rules. In this paper, a Junction Point is defined as the intersection point of the three or more line segments and a Fast JP detector is proposed. The Junction Points of the palm vein line segments associated with their directions of palm vein are computed. Transition number is used to detect the junction function. The edge segments are thinned using a morphological operation. Then we test whether the centre pixel within a 3x3 neigh-bourhood is a junction.

The orientation of a junction point is described as a code of the surrounding pixel of a junction point in the edge image. Pixels in the 5 u 5 regions of the junction point P in Table 1 are numbered as:

Table .1 Pixels in the 5 u 5 regions of the junction point P

P9	P10	P11	P12	P13
P24	P1	P2	P3	P14
P23	P8	P	P4	P15
P22	P7	P6	P5	P16
P21	P20	P19	P18	P17

The orientation code of P is defined as a vector
$f(P_1)f(P_2)f(P_3)f(P_4)f(P_5)f(P6)f(P_7)f(P_8)f(P_9)\ldots f(P_{24})$

The matching algorithm is as follows.
Step 1: Take an unchecked point b in Q
Step 2: Check for the presence of point in a around b in P. If yes, add the point to a go step 3. Else, goto step 1.
Step 3: Check for candidate points, a, with similar code with b. If yes, a and b are the c step 1.
Step 4: Repeat step 1-3 until all points in Q have been checked

MODULE 2 : (Hand Geometry)
The length, width, perimeter and area of all 5 fingers are noted and the width of the palm for the input image is noted and compared with the images in the database.

3-D Hand Geometry
3-D features extracted from the cross-sectional finger segments have previously been shown to be highly discriminatory and useful for personal identification. For each of the four fingers (excluding thumb), 20 cross-sectional finger segments are extracted at uniformly spaced distances along the finger length. Curvature and orientation (in terms of unit normal vector) computed at every data point on these finger segments constitute the feature vectors.

2-D Hand Geometry
2-D hand geometry features are extracted from the binarized intensity images of the hand. The hand geometry features utilized in this work include—finger lengths and widths, finger perimeter, finger area and palm width. Measurements taken from each of the four fingers are concatenated to form a feature vector. The computation of matching score between two feature vectors from a pair of hands being matched is based upon the Euclidean distance.

V. CONCLUSION

This project investigated a novel approach for human identification using palm-vein images. We propose a novel preprocessing, enhancement and feature extraction techniques that can effectively accommodate the potential image deformations, translational, and rotational variations. This approach performs very well even with the minimum number of enrollment images (one sample for training). The palm vein identification method shows its robustness and superiority. The junction point approach extracts palm-vein features by analyzing the junction point of the palm image also achieves reasonably superior performance, and at the same time provides a smaller template size as compared to other methods. Three vein intersecting points are considered. The coordinates of such three points are noted and the distance between the three points are noted. These three points and the distances, of the input image are compared for the images in the database. Since junction point of the vein is different to each induvial, Centroid for the three. In Hand Geometry the length, width, perimeter and area of all 5 fingers are noted and the width of the palm for the input image is noted and compared with the images in the database.

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