Dorsal Hand Vein Biometry by Independent Component Analysis

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Abstract— **Biometric authentication provides a high security and reliable approach to be used in security access system. Personal identification based on hand vein patterns is a newly developed recent year. The pattern of blood veins in the hand is unique to every individual, even among identical twins, and it do not change over time. These properties of uniqueness, stability and strong immunity to forgery of the vein patterns make it a potentially good biometric trait which offers greater security and reliable features for personal identification. In this study, we have used the BOSPHORUS hand vein database which has been taken under a source of NIR infrared radiation. For feature extraction we applied appearance based method ICA which produces independent components. To control over the number of independent component we preprocessed data by PCA before applying ICA, and gives good experimental results.**

Keywords- **dorsal hand vein, ICA, subcutaneous vein detection, BOSPHORUS hand vein database.**

I. Introduction

In this globalized and ubiquitous society, personal or identity verification is now a critical key. Traditional method uses personal identification number (PIN), password, key smartcards, etc which are based on something the user has and/or knows (ownership and knowledge based factor). Today, these methods have proven adequately to be unreliable and do not provide adequately strong security. Due to this fact, biometric authentication has emergently gaining popularity as it provides a high security and reliable approach for personal authentication [1]. Biometrics is science of recognizing a person using physical and/or behavioral features that stays constant throughout one's lifetime and are difficult to fake or change. Many biometric such as face, fingerprint, iris and voice have been well studied and developed. Biometric identification system based on hand vein pattern now a day's gaining popularity as they contain properties like universality, stability and strong immunity to forgery.

Vein patterns are the vast network of blood vessels underneath a person's skin. The shape of vascular patterns in the dorsal region of the hand is unique to an individual even for identical twins, and it claimed to remain stable over long periods of time of individual's life time. As veins are hidden underneath the skin surface and are mostly invisible to human eye, they are not prone to external distortion. The vein pattern is difficult to forge and therefore offers itself as a promising biometrics. The vein pattern not prone to external distortion like scars, pigmentation, burns.

II. NIR IMAGING FOR VEIN STRUCTURE

Looking towards the electromagnetic spectrum Human eyes can only detect visible light, which is a very narrow band (approx. 400 - 750nm wavelength) of the entire electromagnetic spectrum. Human vein patterns beneath the skin, visibility under normal visible light conditions is quite low. However, by using Near-Infrared (NIR) imaging techniques (about 750 to 2000 nm) and Far-Infrared (FIR) (about 6 to 14 μm) we can image the vein pattern of hand. As FIR is thermal imaging technology it is prone to human body condition like after doing exercise or work vein image get change. It has been concluded that using Near-Infrared (NIR) imaging techniques (about 750 to 950 nm) is band that can be used for imaging of vein structure. Two special attributes of infrared radiation and human veins lead to the development of vein pattern imaging methods:

1) The incident infrared light can penetrate into the biological tissue to approximately 3mm depth.

2) The reduced hemoglobin in venous blood absorbs more of the incident infrared radiation than the surrounding tissue.

Therefore by shining an infrared light beam at the desired body part, a charge coupled device (CCD) camera with an attached IR filter can be used to capture an image of veins near to body Surface. The vein patterns near the skin surface appear darker than the surrounding parts and are easily discernible

In healthy individuals, NIR light is mostly absorbed by blood pigments in deep tissue which does not heat up due to constant circulation. Hence, light in the NIR region does not present the risk of tissue damage that occurs at wavelengths longer than 950 nm [3].

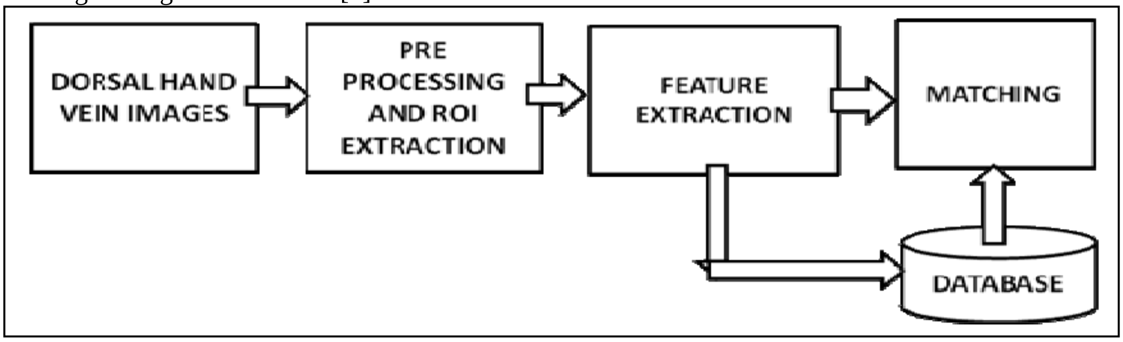

Fig.1. Block diagram of dorsal hand vein biometry

III. DESCRIPTION OF DATABASE

The BOSPHORUS hand vein database has been released by BOGAZICI UNIVERSITY Istanbul, Turkey[12]. In this database NIR imaging technology and reflection method have been chosen for image acquisition. BOSPHORUS hand vein database contains 1200 images of left hands of 100 different people in which 42 are female and 58 are male from the age varying between 16- 63.. Each subject underwent four imaging sessions that consisted of the left hand

1. Under normal condition (N: Normal),
2. After having carried a bag weighing 3 kg. for one minute (B: Bag),
3. After having squeezed an elastic ball repetitively (closing and opening) for one minute (Activity: A),
4. After having cooled the hand by holding an ice pack on the surface of the back of the hand (Ice: I).

In each session there are three images, which resulted in 3×4 = 12 images per subject of his left hand under four different conditions. Images of the left hands of 20 subjects after a time lapse ranging from two months to five months has been included in this database. The image size is 300×240 pixels with a gray scale resolution of 8 bit per pixel.

IV. PREPROCESSING AND ROI EXTRACTION

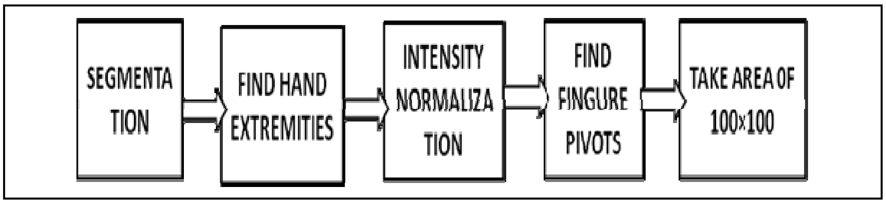

Figure .2.Steps for ROI extraction

Hand images captured in arbitrary poses and postures. In order to match hand veins correctly, pose normalization is necessary. First we have flipped image from left to right. Global translation to the centroid of the hand such that it coincides with the center of the image and rotation of hand toward the direction of the larger eigenvector that is the eigenvector corresponding to the larger eigen value of the inertia matrix is necessary.

A. Hand Segmentation

Hand segmentation aims to extract foreground i.e. hand region from background. K-means clustering algorithm has been used to separate the hand foreground and the lighter background. For K-means clustering as we need to separate hand from background we have taken K=2 i.e. two clusters. This result in to image having holes and isolated foreground blobs. After finding out connected components in the image, it can be seen that the maximum connected component is the hand itself, and then remove the debris by using area-based size filtering.

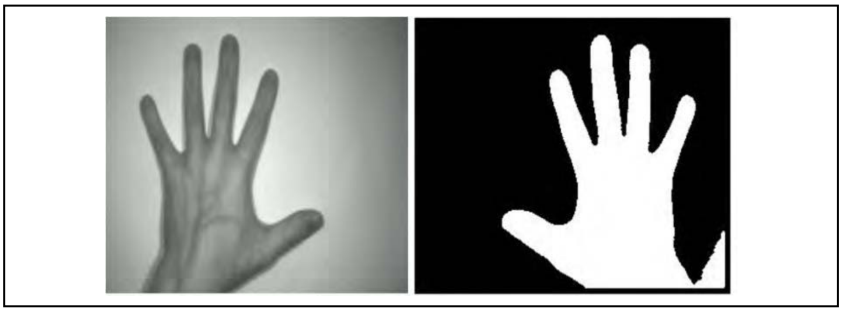

Figure 3.(a)Exemplary image (b) segmented image

B. Find Hand Extremiteis

Detecting and localizing the hand extremities, that is, the fingertips and the valley between the fingers is the main step for ROI extraction. Since both types of extremities are characterized by their high curvature, we first experimented with curvegram of the contour, that is, the plot of the curvature of the contour at various scales along the path length parameter [11].

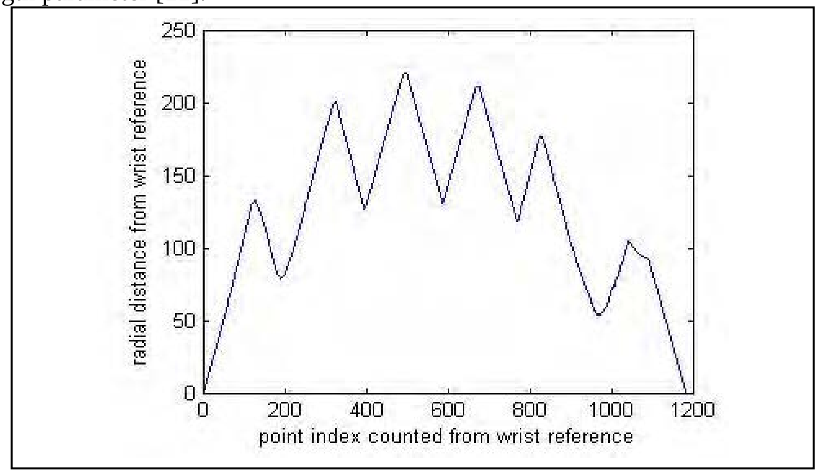

Figure.4.Curvegram of contour

The maxima are the peaks of hand and minima are the valley points. We have taken the first five maxima as the peaks of hand in sequential manner like thumb, index finger, middle finger, ring finger and little finger. Remaining peaks are the noise and we discard it. Three missing valleys are found as 10% more distant than adjacent valley.

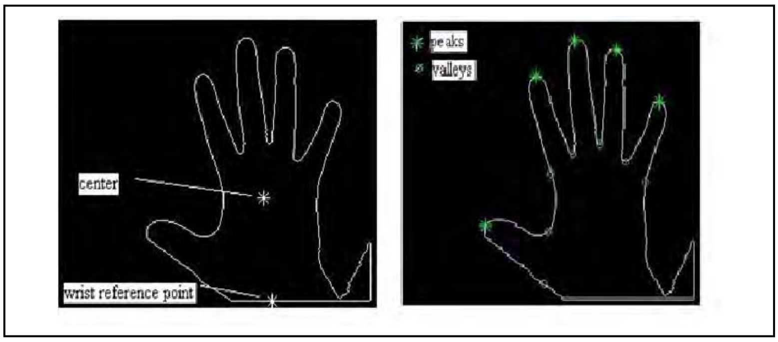

Figure. 5. (a) Contour of hand (b) peak and valleys

C. Intensity Normalization

In image processing, normalization is a process that changes the range of pixel intensity values. By normalizing standard deviation and mean of the foreground pixel to 1 texture variance has been enhanced.

Figure.6.Normalized hand

D. Find Fingure Pivot

Fingers rotate around the joint between proximal phalanx and the corresponding metacarpal bone. These joints are somewhat below the line joining the inter finger valleys. Therefore, the major axis of each finger is prolonged toward the palm by 20% in excess of the corresponding finger length. These points are the figure pivots. To locate ROI by joining index figure pivot to the little figure pivot and to thumb pivot as shown in Fig. 7(a).

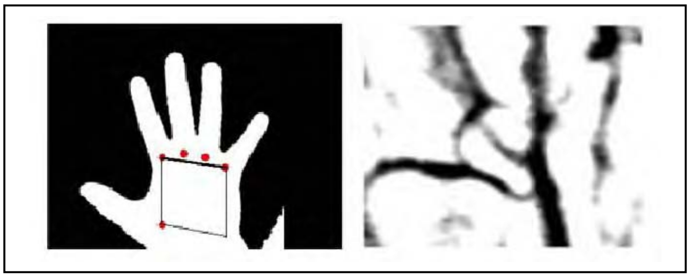

Fig.ure 7. (a) figure pivots (b) ROI

V. FEATURE EXTRACTION

Feature extraction techniques are an important part of hand vein recognition system with a crucial impact on the performance of system. As appearance based technique is generative and easy to characterize than geometry based technique we have projected dorsal hand in NIR band to subspace via ICA. Independent Component Analysis (ICA) is a technique for extracting statistically independent variables from a mixture of them [7]. ICA intimately related to the blind source separation (BSS) problem, where the goal is to decompose an observed signal into a linear combination of unknown independent signals. Let s be the vector of unknown source signals and x be the vector of observed mixtures. If A is the unknown mixing matrix, then the mixing model is written as

$$x= As \qquad (1)$$

It is assumed that the source signals are independent of each other and the mixing matrix A is invertible. Based on these assumptions and the observed mixtures, ICA algorithms try to find the mixing matrix A or the separating matrix W such that

$$U=WX \qquad (2)$$

Where U is the estimation of s. There exist two possible formulations of ICA. In the first architecture, called ICA1, each of N individual hand-data vectors is assumed to be a linear mixture of an unknown set of N statistically independent source hands. In the second architecture, ICA2, the superposition coefficients are assumed to be statistically independent, but not the basis images. ICA2 produces global features in a sense that every image feature is influenced by every pixel, ICA1 architecture has been preferred in this work as it produces spatially localized features that are only influenced by small part of image. Accordingly, each of K pixels of the hand images result from independent mixtures of random variables. Eq. 1 still holds but x_i and u_i form columns of a K×N matrix. The data vectors fed into the ICA analysis are the lexicographically ordered hand image pixels. The dimension of these vectors is K = 10000, for our region of interest of size 100×100 in vein images. ICA finds a matrix W such that the rows of U=WX are as statistically independent as possible.

The number of independent components (ICs) by the ICA algorithm corresponds to the dimensionality of the input. Means, if we have 100 images in the training set, the algorithm would attempt to separate 100 ICs, and it increases with number of person. In order to have control over the number of ICs extracted by the algorithm, instead of performing ICA on n original images, we performed

ICA on a set of m linear combinations of those images, where n<m. Recall that the image synthesis model assumes that the images in are a linear combination of a set of unknown statistically independent sources. The

image synthesis model is unaffected by replacing the original images with some other linear combination of the images. Bartlett and colleagues first apply PCA to project the data into a subspace of dimension m to control the number of independent components produced by ICA [8][9].Pre-applying PCA enhances ICA performance by 1) discarding small trailing eigen values before whitening and 2) reducing computational complexity by minimizing first and lower order dependencies. As we know PCA gives the linear combination of images that accounts for maximum variability in pixels.PCA do not throw away the high order relationship. This relationship still exists in data that would be given to ICA.

Let P_m denotes the matrix containing the first m principle components in its columns, where m<n. we performed ICA on P_m^T producing a matrix U which contains m independent source images in its rows. As said The ICA algorithm learns the weight matrix W, which is used to recover a set of independent basis images in the rows of U. before applying ICA algorithm on the data it is very useful to do some preprocessing like centering and whitening. The most basic and necessary preprocessing is to center P_m^T, i.e. subtract its mean vector $\mathbf{m} = E\{P_m^T\}$ so as to make P_m^T a zero-mean variable. Another useful preprocessing strategy in ICA is to first whiten the observed variables. This means that before

the application of the ICA algorithm (and after centering), we transform the observed vector linearly so that we have obtain a new vector x which is white, i.e. its components are uncorrelated and their variances equal unity. For whitening purpose we have used EVD (Eigen Vector Decomposition) . This data is called sphere data. There are several algorithms that iteratively approximate **W** so as to indirectly maximize independence. These algorithms iteratively optimize a smooth function whose global optima occur when the output vectors **u** are independent.

1. InfoMaxrelies on the observation that independence is maximized when the entropy H(u) is maximized
2. The *JADE algorithm* minimizes the kurtosis of $f_u(u)$, since minimizing kurtosis will maximize statistical independence.
3. *FastICA*is maybe the mostgeneral, maximizing negentropy.[7]

In this work we have used FastICA algorithm to find W. When the input to ICA are sphered data, the full transformed matrix W_I is the product of sphereing matrix whitening matrix (W_Z) and matrix or learned by ICA.

$$W_I = WW_Z \tag{3}$$

The principal component representation of the set of zero-mean images in X based on P_m is defined as

$$R_m = X * P_m \tag{4}$$

A minimum squared error approximation of X is obtained by

$$X_{rec} = R_m * P_m^T. \tag{5}$$

ICA algorithm produces learned matrix $\mathbf{W_I}$. Basis image or independent component can be defined from Eq. 2

$$W_I * P_m^T = U \tag{6}$$

which represent principle component as

$$P_m^T = W_I^{-1} U \tag{7}$$

Putting these values in Eq. 5

$$X_{rec} = R_m * W_I^{-1} U \tag{8}$$

Where X_{rec}represents reconstructed image or minimum squared error approximation of X like ICA.The IC representation of the face images based on the set of statistically independent feature images, was, therefore, given by the rows of the matrix

$$ICA\_FEATURES = \mathbf{A}_{test} = R_m * W_I^{-1} \tag{9}$$

In recognition stage, we assume that test set follows the same synthesis model with the same independent components. A representation for test images is obtained by using the principal component representation based on the training images

$$Rtest = X_{test} * P_m \tag{10}$$

$$ICA\_feature_{test} = A_{test} = R_{test} * W_I^{-1} \tag{11}$$

VI. FEATURE MATCHING

In the identification mode, the user does not provide any identity claim, but the system must find out the user's identity from a database of enrolled users. For a person verification task, one must differentiate the genuine hand from the impostor. We measure the distance between the test feature vector and all the feature vectors in the database belonging to N different subjects. For this purpose, the distances between the hand of the applicant and all the hands in the database are calculated and the scores are compared against a threshold. In this work we have used cosine similarity measure (CSM). An individual to be tested is simply recognized as the person i^* with the closest feature vector b_{i*} [10] , where distance is measured in terms of cosine of the angle between them

$$i^* = \arg max_i \left\{ \frac{a_i \cdot a_{test}}{\|a_i\| \|a_{test}\|} \right\} \tag{12}$$

VII. EXPERIMENTAL RESULTS

We have taken images of 40 people in normal condition as an enrolled database. As there are 3 images per person we have found out feature of all three images and saved three different feature matrices and each test image is compares with the score of each enrolled image out of three. Threshold has been set in this work as If any of hand score is greater than 0.85 that will be the matched hand Otherwise any two same number hand having score greater than 0.75 that will be the matched hand.

Table 1: Performance of System

	Number Of Test Image	Recognition Rate	Rejection Rate	False Rate
Registrant	120	80%	20%	0%
Non Registrant	30	0%	100%	-

The FAR(False acceptance rate) and FRR(False Rejection Rate) can be find out as

$$FRR = \frac{number\ of\ false\ rejections.}{number\ of\ access} = \frac{24}{120} = 20\%$$

$$FAR = \frac{number\ of\ false\ acceptance}{number\ of\ access} = \frac{0}{40} = 0\%$$

Table 2 shows the time required for each process.

Table 2: Time required per Process

Process	**Average time required in sec**
Preprocessing and ROI extraction(for 1 image)	0.4613
Feature extraction(of 40 images)	8.5775
Feature matching	0.0044

VIII. CONCLUSION

It can be concluded that hand vein features having characteristics like Universality, Distinctiveness, Permanence, Collectability, Acceptability, Circumvention, and Performance.

We have collected BOSPHOROUS hand vein database, which has used infrared imaging technology and has taken under adverse conditions mirroring real life situations. The appearance based features are extracted using Independent component analysis, and adapted ICA technology by PCA to control over the number of independent component. This makes the process faster.

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