Dorsal Hand Veins Based Biometric Identification System Using Multiple Classifier Methods

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Abstract. Biometric identification systems offer a high level of security by using reliable, difficult-to-change parameters. Identification systems have become biometric based, especially with the increase in the performance rates of machine learning methods. The indistinguishable terminology used here for feature extraction is based on QIF (Quadratic Inference Function). We used multiple classifiers in our research paper i.e. SVM, ANN, LDA + KNN, and CNN methods. Bosphorus University get available the hand vein database which is used for the evaluation purpose. After investigations with the QIF feature extraction techniques, it can be decided that CNN performs outstanding performance on hand vein images, After evaluation we get 99.64 percent recognition rate.

Keywords: Dorsal,Vein Minutiae,LDA,KNN,Euclidean distance,CNN,SVM

1 Introduction

Due to unreliability of most of the old verification approaches like PINS, passwords, private and public keys, password encryption decryption methods, peoples are more attracted towards the Biometric systems in the research community[1],[2]. The famous biometric systems now a days are Iris, DNA, palm veins, hand geometry, ear geometry and texture. Biometric which comprises the study of human biological, physical and behavioural characteristics is being established to confirm more reliable safety. Lately dorsal hand vein pattern biometric is inviting the courtesy of researchers and is gaining momentum. Many scientist in the medical field proved that vascular pattern in the back of the hand id unique from person to person[3], [4], [5]. Many researchers are get attracted towards the vein recognition due to its steadiness, individuality and resistance to fake because dorsal veins are under the skin and not seen to naked eyes. So that helps us to make one reliable biometric system [1]. Sometimes extreme temperature and aged skins slight effect on the dorsal hand vein image, unlike iris and voice feature gaining [6]. The dorsal hand vein biometric system is natural to verify the identity of individuals. In the human life cycle as human being grows, shape of vein pattern is not changed, It is remain constant. Image acquisition, segmentation, finding features and classification are the phases where every biometric system goes, the finding and extracting features is very difficult task and that mainly influence the concert of the biometric system. In our research, QIF (Quadratic Inference Function) [8],[9] is used to extracting the feature. Adaptive estimating equation or QIF combines the covariance matrix and the vectors in the training set. Later in the paper having some sections. section 2 highlights existing techniques for hand vein recognition. Section 3 indicates description of our work 4.finally summarise the work.

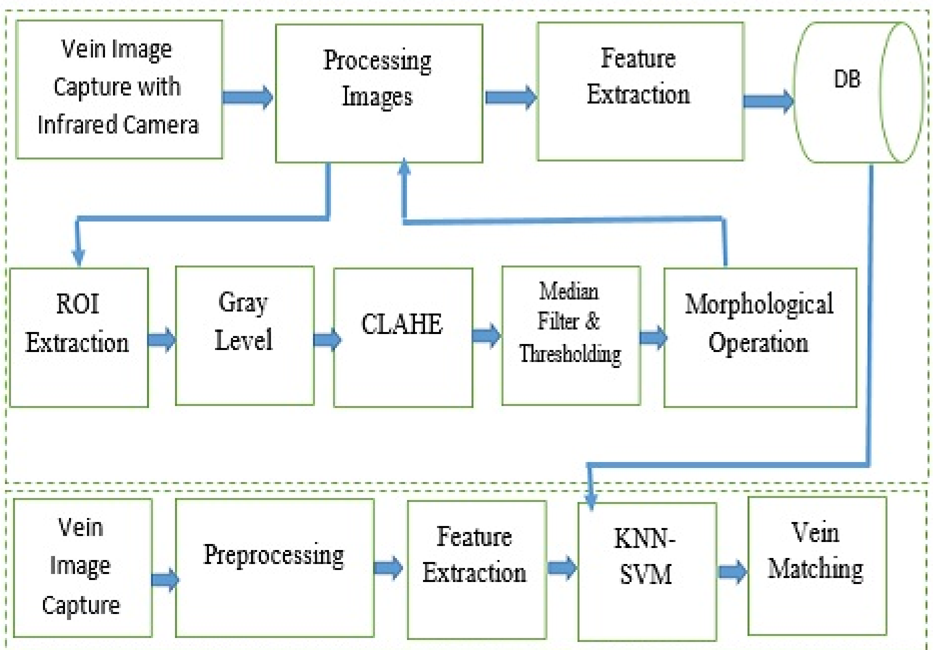

Fig. 1. Flow of our system

2 Correlated Works

A number of techniques have been presented by different researchers for hand vein recognition. Lee J.C et al. [1] propose a dynamic pattern tree to accelerate matching performance and evaluate the discriminatory power of these feature points for verifying a person's identity. Chuang, SJ et al. [2] proposed endpoints-tree (EP-tree) that accelerate the matching performance and evaluate the discriminating power of these end pointsfor person verification purposes. Ahmad MA et al.[3]used stack of natural image patchesas filters and transform an image into integer labels describing the small-scale appearance of the image. Dhrit, Kaur M [4] fuses the two traits at feature extraction level by first making the feature setsture sets compatible for concatenation and then reducing the feature sets to handle the "problem of curse of dimensionality". Yakno M. et al.[5]proposed two methods in two different stages; grayscale enhancement and binary enhancement for correction of low contrast and noisy images. Pontoh F.J. [6] has been explored and implemented feature extraction method called Local Line BinaryPattern(LLBP) and successively verified personal. Kumar A.[7] demonstrated new approach for palmprint recognition using discreate cosine coefficients, which can be directly obtained from the camera hardware. Waghode A.B.[8] used Gabor filter in preprocessing for removing the noise from acquired image then they used PCA for feature extractionand then LDA as well as KNN classifier for matching purpose.

3 Vein image preprocessing

Commonly, images of dorsal hand vein which is collected from different sources contains unuseful info like knobs and limbs, which was unuseful for this research. The acquired images could not be used because 1. Quality of image caused by non-similar and non-stable illumination. 2. Noise present in the image. 3. Obtained geometrical variations in hand poses due to scale, rotation and shift So, in this research, before going to segmentation of dorsal hand vein images, preprocessing methods were applied.To confirm that main features important to hand orientation were preserved, for obtaining regions of interest (ROI) from hand vein images, geometric correction was done. Image normalisation and filtering were done which are the methods of Grey-level processing. To widen image contrast for segmentation of vein structure (Image enhancement) and area surrounded by skin also furnished.Hence, all template windows used in filter were set to 15 X15 pixels. The setting of this template window size was to retain as much vein information as possibleand reduce noise information. The filtered results of images are shown in figure 2. All filtered results were further mea-sured by calculating their TV(Table). In this work, the wiener filtering was used as it had the lowest TV value. A pixel-wise adaptive Wiener method was applied based on statistics estimated from the local neighbourhood of each pixel [14]. It estimates the local mean.

$$\mu = \frac{1}{NM} \sum_{n1,n2 \in \eta} a\left(n1, n2\right) \tag{1}$$

$$\sigma^2 = \frac{1}{NM} \sum_{n1,n2 \in \eta} a^2\left(n1, n2\right) - \mu 2 \tag{2}$$

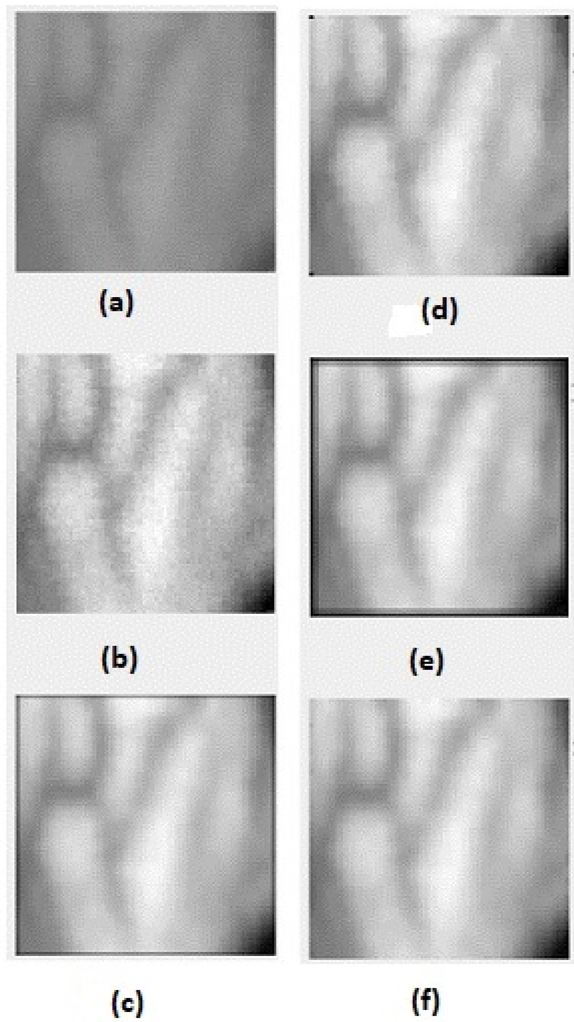

Fig. 2. Results image filtering:a) Source Image b) normalised image c)mean filter d) Median filter e) gaussian filter f) wiener filter

Where η is the N-by-M local neighbourhood of each pixel in the image A. Then a pixel wise wiener filter is created using these estimates,

$$b(n1,n2) = \mu + \frac{\sigma^2 - \nu^2}{\sigma^2}((a(n1,n2) - \mu)) \tag{3}$$

Where v^2 is the noise variance. In this work, as the noise was not known, the average of all the local estimated variances were used.

Table 1. TV values comparision

Before Filtering	**After Filtering**			
	Median	**Mean**	**Wiener**	**Gaussian**
TV 101747.9	81429.7	78588.1	76910.7	89552.3

To enrich contrast between hand skin and vein underneath the dorsal part CLAHE method wad applied. the following expression illustrates phenomenon of CLAHE.

$$hL\left(a\right) \, = \alpha hw\left(a\right) \, + \, \left(1-\alpha\right)hG\left(a\right) \; 0 \le \alpha \le 1 \tag{4}$$

Where α is the confined weightiness; hG(a) is the histgramafter normalisation through the exiting window; $hw(a)$ is histogram after normalisation through the internal window;$hL(a)$ is the half-done standardized histogram. For segmentation some methods were examined including maximum curvature, niblack and otsu but we used maximum curvature for good vein pattern. This method reserve main features that obtains center point of all vein patterns [15]. ROI image is represented as F, Pf (z) is a profile, position represented by z and curvature specified as c(z):

$$c\left(z\right) = \frac{d^2 P_f\left(z\right)/dz^2}{\left[1 + \left(dP_f\left(z\right)/dz\right)^2\right]^{\frac{3}{2}}} \tag{5}$$

The maximum points represented by N. A score Scr(z), illustrated as:

$$Scr(z_i{}') = c(z_i{}') \times W_r\left(i\right) \tag{6}$$

Where,Wr(i) is the width of the region where the curvature is positive and one of the zi is located. The width and the curvature of regions are considered in their scores, which are assigned to a plane, V, that is:

$$V(x_i{}', y_i{}') = V(x_i{}', y_i{}') + S_{cr}(z_i{}') \tag{7}$$

All profiles are analysed in four directions: horizontal vertical and vertical at 45 degree. Then, all centre positions of the veins are located. Lastly connect vein center by checking two neighbouring pixels on the right and left sides of pixel (x,y). An operation is then applied to all pixels, represented as follows:

$$G_{d1}(x, y) = min\left\{max\left(V\left(x+1, y\right), V\left(x+2, y\right)\right) + max\left(V\left(x-1, y\right), V\left(x-2, y\right)\right)\right\} \tag{8}$$

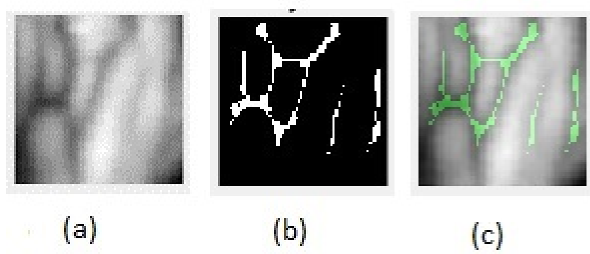

Fig. 3. Segmentation using maximum curvature. a) original imagey b)binary image c)Maximun curvature of image.

4 Proposed method used for recognition of dorsal hand veins

After segmenting the hand vein using maximum curvature method some unwanted regions like spots, holes and burrs are occurred those are removed by some morphological techniques [16]. Postprocessing removes unwanted regions from the image.

4.1 Feature Extraction

After obtaining the vein pattern, the coordinates were extracted from the pattern. Each coordinate represent the pixel values of the image We assume I images for the training set X, i.e,

$$X = \left[X1, X2, ... \; Xi, ... \; XI\right]$$

$$Xi = \begin{bmatrix} Xi1,1 & Xi1,2 & \cdots & Xi1,N \\ Xi2,1 & Xi2,2 & \cdots & Xi2,N \\ \vdots & \vdots & \ddots & \vdots \\ XiM,1 & Xim,2 & \cdots & XiM,N \end{bmatrix}$$

where i is the index for the i^{th} image, j is the corresponding index for the x -coordinate of the i^{th} image, k is the corresponding index for the $-$ y coordinate of the i^{th} image where i=1,...,I,j=1,...,M and k=1,...,N. Thus, the training matrix X is of dimension Mx2NI. Note that for each image Xi in the training set X , the number of x co-ordinates is chosen using the condition M=min(M1,M2...,Mi,...,MI) ,where Mi= the number of x co-ordinates in image i and the number of y co-ordinates is chosen using the condition N = min(N1,N2,...,Ni,...,NI) ,where Ni=is the img points on axis y . If you remain dimenssionality of Xi as it is those two conditions were necessary.

But, this method produces some disadvantages when the training set is expressed this way, 1) some dissimilarity produces in element of the training set 2) if Image is big then matrix is also bigger. So, that produces trouble to work on the source training matrix X. The solution of those type of complications, need to normalize the coordinates by making averaging.

4.2 Feature Matching

To check the correctness and proficiency of our projected method, FAR and FRR are calculated. In our research work QIF used. It observed that QIF is useful for eliminating some disadvanteges when some dissimilarity produces in element of the training set and if Image is big then matrix is also bigger. So, that produces trouble to work on the source training matrix X [18]. The table below shows the FAR and FRR for 200,400,600,800 and 1000 images tested.

Table 2. FAR and FRR Comparision using QIF.

Number of Images	**FAR**(%)	**FRR**(%)
200	0.0600	0.0700
400	0.0350	0.0600
600	0.0340	0.0340
800	0.0230	0.0145
1000	0.0200	0.0300

According to the results obtained, the FAR and FRR is less when using quadratic inference function.

4.3 Classification

In first classifier method The QIF features are classified with KNN classifier 81.61% Accuracy rate is obtained with the KNN classifier after iterating multiple experiments. In the following all experiments 80% of the dataset is used for training and 20% for testing purposes. In second classifier method combined PCA + KNN classifier and performed some measurements. According to the result obtained, the accuracy rate is 76.41. In third classifier method CNN is the classifier, with CNN classifier we classified our feature set and in the result evaluation we obtained 99.64 accuracy rate. The following table shows result analysis.

Table 3. Performance metrics using different classifiers

Classifier	**Accuracy**(%)	**Precision**(%)	**Recall**(%)	**Specificity**(%)
KNN	0.8161	0.8404	0.8161	0.9981
PCA + KNN	0.7641	0.7844	0.7641	0.9976
CNN	0.9964	0.9964	0.9964	1.000

5 Experiment results and discussion

For our experiment standard database is used, the database obtained from bosphorous university [20]. Database having 1200 images of 100 subjects, but in our experiment 1000 images were used because in preprocessing remaining 200 images are not clear so they are not able to detect the features. We divided 80% of images for training and 20% images for testing. all those images are selected randomly to reduce biasness and that experiment repeated 11 times. In first classifier method The QIF features are classified with KNN classifier 81.61% Accuracy rate is obtained with the KNN classifier after iterating multiple experiments[19]. In second classifier method combined PCA + KNN classifier and performed some measurements. According to the result obtained, the accuracy rate is 76.41. In third classifier method CNN is the classifier, with CNN classifier we classified our feature set and in the result evaluation we obtained 99.64 accuracy rate. The following table shows result analysis.

6 Conclusion

The maximum curvature method for vein extraction is a noble option for segmentation as compared to german filter which is used in our previous research paper and In the comparision of KNN, PCA + KNN and CNN, CNN achieved the 97.83% highest accuracy. In incoming days experiment with CNN + KNN is the goal.

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