International Journal of Education and Science Research Review

E-ISSN 2348-6457
Volume-9, Issue-1 Jan-Feb-2022
P-ISSN 2349-1817
www.ijesrr.org
Email- editor@ijesrr.org

STUDY ON DORSAL HAND VEIN AUTHENTICATION SYSTEM

More Kiran Ananda
Research Scholar
School of Science & Technology
Glocal University Saharanpur (U.P)

Prof.(Dr.) Rakesh. K. Yadav
Research Supervisor
School of Science & Technology
Glocal University Saharanpur (U.P)

ABSTRACT: The dorsal hand vein pattern is unique biometric identity of the human beings which is used for authentication purposes in various applications. The vein pattern hidden under the skin is quite different in persons, even for identical twins and remains stable over long period of time. The aim of this project is to recognize the person using dorsal hand vein authentication system for high security applications. According to different researchers, vein biometric is a good biometric trait among other biometrics such as fingerprint, palm and finger veins, eyes, voice, signature, gait and DNA for authentication systems. A dorsal hand vein authentication system consists of the following steps: Image acquisition and pre-processing, finding of region of interest, extraction of dorsal hand vein pattern features and recognition and authentication is done using similarity matching. This method is used to improve the accuracy and response time of dorsal hand vein recognition and authentication and use neural networks for the final evaluation of the testing sample and training samples to recognize the person.

KEYWORDS: Biometrics, Dorsal hand Vein, ROI, Feature Extraction.

I. INTRODUCTION

Biometric technology isone of the efficient personal authentication and identification technique. Biometric is the term used in computer science to refer to the field of mathematical analysis of unique human features such as fingerprint, palm and finger veins, eyes, voice, signature, gait and DNA. Biometric solutions have witnessed an accelerated pace of growth in the global market of security over the past decades, mainly by increasing requirements in public security

against terrorist activities, sophisticated crimes, and electronic frauds. Biometrics is the science of identifying a person using their behavioural and physiological features. Biometrics systems are classified in two categories as physical and behavioural. Physical systems are related to the shape of the body such as fingerprints, face recognition, DNA, vascular patterns, iris of the eye, vein pattern etc. Behavioural biometrics system are related to behaviour of a person like voice, gait, signature, etc. We focus on the vein pattern of the back of the hand (i.e., dorsal hand) because it is distinctly visible, easy to acquire, and efficient to process.As compared with other popular biometric traits, such as face or fingerprint, the dorsal hand vein has several distinguished merits. It is also a best variant to biometric systems that require physical contact with the machine because it extracts the vein pattern, with the hand not in contact with the device instead hand can easily stretched and the capturing of vein pattern can be easily carried out. Since the system is based on three features such as live body, internal veins and non-contact type, there is no possibility for forgery, and no misuse by evildoers, thus it can be used at places requiring high level of security to avoid crimes and frauds.Fig.1shows the figure of dorsal hand vein pattern.

Fig.1 Dorsal hand vein pattern

II. RELATED WORK

(1) In paper, 'Human identification using palm-vein images', Y. Zhou and A. Kumar. In this paper,the author has given a Statistical-based methods employ statistical information, such as the local binary histogram and moments, and can be categorized into global and local statistics methods. For example, local statistical based methods include local binary patterns (LBPs), local derivative patterns (LDPs), and their variantswhich are also sensitive to scaling, rotation, and displacement. Global statistical-based methods consist of invariant moments, which are invariant to scaling, rotation, and displacement, wavelet moments, gradient fields, and so on.

(2) In paper, 'A finger-vein verification system using mean curvature,' W. Song, T. Kim, H. C. Kim, J. H. Choi, H.-J. Kong, and S. R. Lee.In thispaper,the author has given a Geometry-based methods which are derived from fingerprint and palmprint recognition that utilize approximate line-like, curve, and point information, which are highly dependent on the chosen coordinate system. Hence, the region of interest (ROI) extraction and position calibration must be considered in advance. Generally, geometry features pose difficulties in extraction, representation, and matching, as well as suffer from information loss owing to small and/or blurred textures. Therefore, these methods have poor distinguishing ability and are also sensitive to scaling, rotation, and displacement.

(3) In paper,'Contact-free palm-vein recognition based on local invariant features,' W. Kang, Y. Liu, Q. Wu, and X. Yue. In this paper, the author has given a Local invariant-based methods, inspired by the approaches emerging from computer vision, such as SIFT, SURF, ORB, extract local invariant features directly rather than first employing preprocessing. However, owing to the lack of greyscale shift and corners, the number of extracted local invariant feature points is small and also exhibit large intraclass changes; therefore, some image enhancement should be performed before local invariant tbased methods are adopted for palm vein identification.

(4) In paper, 'Personal authentication through dorsal hand vein patterns,' C.-B. Hsu, S.-S.Hao, and J.-C. Lee, In this paper,the author has given a Appearance-based (subspace-based) methods , including PCA, LDA, ICA, NMF, and their kernel version, manifold method (OPNN), take subspace coefficients as features without prior knowledge. These can be separated from the above mentioned methods and viewed as an issue in the pattern recognition domain. Appearance-based methods are utilized for feature extraction, adopting both artificial intelligence and machine learning methods for classification.

III.PROPOSED METHOD

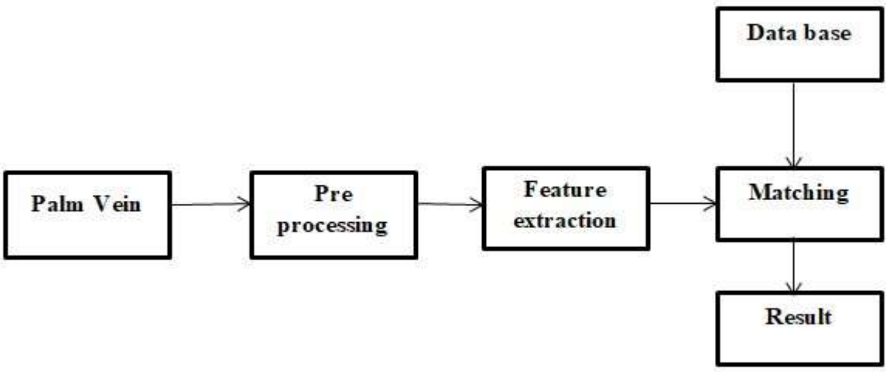

Fig.2 Proposed method

The development of the proposed Palm-Dorsal vein biometric identification system is discussed in three parts: the pre-processing stage, feature extraction and matching the data base with the processed image. Image processing designs requires the image pre-processing and segmentation to be performed before any further image processing and feature extraction process can be conducted. Pre-processing involves algorithms that include region of interest (ROI) extraction, image enhancement (denoising), and image normalization (resizing). The segmentation process transforms the original image into a meaningful representation makingit easier to analyze. Feature Extraction is the process of extracting the feature from the image which is needed. Then, the feature extracted image and the data base image will be matched for the identification and the result will be concluded. Fig.2 shows the proposed method.

IV.METHODOLOGY

Process

The following are the process of the proposed system,

i. Image Acquisition
ii. Pre processing
iii. ROI Extraction of Palm Vein
iv. Palm Feature extraction using LBP
v. Fusion of Biometric Features
vi. Matching based on Artificial Neural Network
vii. Matching result

Step 1: Image Acquisition: Image Acquisition is a process getting an input image for the process mangroves species classification using image processing algorithms.

Step 2: Pre processing: The aim of pre processing is an improvement of image data that suppress unwanted image data distortions or enhance the some image features important for the further processing.

Step 3: ROI Extraction of Palm Vein with Adaptive K means: Region of interest (ROI) extraction is an important step in deriving visual features for an audio-visual speech recognition system. Colour based segmentation offers the potential of computationally inexpensive algorithms for Region OfInterest selection. It presents a comparative study of two colour based techniques, one using hue and accumulated difference, the other chrominance. The original image of palm vein will do the grey-scale processing, and it becomes a common grey image. The grey image will do binarization processing, and palm region and the background are separated. Based on centroid algorithm, the centroid of the image is extracted. We take the centroid as the center origin and mark a rectangle which will be intercepted. The 256×256 sub image is cut out in grey image, and so the ROI image of palm vein is obtained.

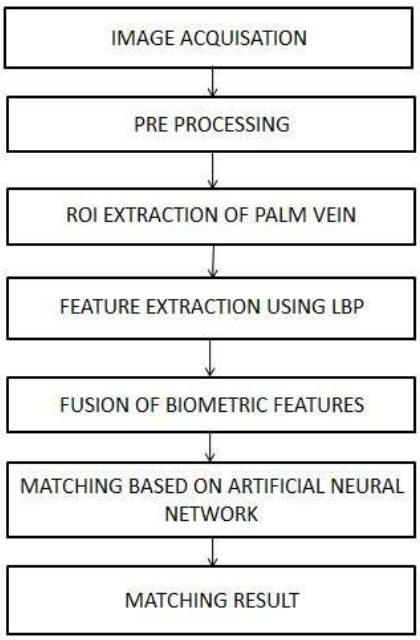

Fig.3 Flow chart

Step 4: Palm Feature extraction using LBP:

Adaptive K means:K-means clustering is a type of unsupervised learning, which is used when you have unlabeled data. This algorithm is to find groups in the data, and the number of groups represented by the variable *K*. The algorithm works iteratively to assign each of the data point to one of *K* groups based on the features that are provided. Data points are clustered based on feature similarity. The results of the *K*-means clustering algorithm are:

- The centroids of the *K* clusters, which can be used to label new data.
- Labels for the training data.

Rather than defining groups before looking at the data, clustering process allows you to find and analyze the groups that have formed organically. The "Choosing K" section describes how the number of groups can be determined. Centroid of clusters is a collection of feature values. Examining the centroid feature weights can be used to qualitatively interpret what kind of group that each cluster represents.

Algorithm: The K-means clustering algorithm uses iterative refinement which produce a final result. The algorithm inputs are the number of clusters K and the data set, and data set is a collection of features for each data point. The algorithms starts with initial estimates for the K centroids, which can either be randomly selected or randomly generated from the data set. The algorithm then iterates between two steps, they are:

1. Data assignment step:Each centroid defines one of the clusters, each data points are assigned to its nearest centroid, based on the squared Euclidean distance. More formally, the collection of centroids in a set, then each data point is assigned to a cluster based on the standard Euclidean distance. Let the set of data point assignments for each cluster centroid.

2. Centroid update step: The centroids are recomputed. This is done by taking the mean of all data points that assigned to the centroid cluster. This algorithm iterates the between steps one and two until a stopping criteria is met. The K-means clustering algorithm is guaranteed to converge to a result. The result may be a local optimum, means that assessing more than one run of the algorithm with randomized starting centroids may give a better result.

Choosing K: The algorithm described above finds the clusters and data set labels for a particular pre-chosen K. To find the number of clusters, the user needs to run the K-means clustering algorithm for a range of K values and compare the results. In general, there is no method to determine exact value of K.

Step 5: Extract Vein using Repeated line Tracking: Repeated line tracking method gives a promising result in finger-vein identification: This method is to trace the veins in the image by chosen directions that according to predefined probability in the vertical and horizontal orientations, and the starting seed is randomly selected; the whole process is repeatedly done for a certain number of times. A cross-sectional profile of a vein will appears as a valley. The depth of the valley varies by the shading in the image. However, the valley remains detectable. This profile gives us a robust method of finger-vein detection.

The line-tracking operation may starts at any pixel in the image. The position of current pixel is called the 'current tracking point' and it is moved pixel by pixel along the dark line. The depth of the cross-sectional profile will be checked around the current tracking point. The current tracking point is on the dark line. The dark line's direction can be detected by checking the depth of the valley. After that, the current tracking point moves to the pixel which is closest to this direction. If the valley is not detectable in any direction, it knows that the current tracking point is not on a dark line and then a fresh tracking operation starts at another position. For a smooth line tracking, an attribute that restricts increases in the global curvature of the locus will be added to the tracking point, that attribute is called 'the moving-direction attribute.If only a single line-tracking operation is conducted, only a part of veins within the image can be tracked with created a problem. To solve this problem, vein-tracking sequences are started at various position, so that the line-tracking trials are conducted evenly across the image. By chance the current tracking point may track a region of noise. Statistically, the dark lines are increasingly tracked more often with repeated operations which make for the robust extraction of patterns of finger veins.

The number of times that each pixel has become the current tracking point will recorded in a matrix which is named as the 'locus space'. The size of the locus space is the number of pixels in the captured images. The total number of trials on which each pixel has become the current tracking point is recorded in corresponding matrix element. Therefore, the locus space element is more frequently tracked has a higher value.

Step 6: Extraction of the finger-vein patterns: The locus space positions where high values are stored are those tracked frequently in the line-tracking procedure. The high values positions in the locus space have high probabilities of being the positions of veins. Therefore, the paths of finger veins are obtained as the chains of high-value positions.

Step 7: Matching Result: The comparison of features between test images and trained images are done to find whether there is a mismatch. When the features of test images and trained images are similar then the required result will be obtained.

V. RESULT AND DISCUSSION

If the image in the data base and the test image were similar then it provides a authentication to a person,

Fig.4 shows the authenticated output. In case, if the image in the data base and the test image were not matched it does not provide authentication to a person.

Fig.5 shows the unauthenticated output.

Fig.4 Authenticated output

Fig.5 Unauthenticated output

VI. CONCLUSION

Dorsal vein patterns are sufficiently different across every individual person, and they are stable unaffected by ageing and no significant changed in adults by observing. It is believed that the patterns of blood vein are unique to every individual, even among identical twins. Dorsal hand vein authentication system can be used in high security areas like military, jail, parliment and so on. Finger print authentication can be hackable, but vein pattern are inside our body it cannot be removable until any serious accident causes. And also it can be used for multiple authentication process.

VII. REFERENCES

[1].B.M.Sontakke, V.T.Humbe, P.L.Yannawar, “Dorsal Hand Vein Authentication System: A Review,” International Journal of Scientific Research Engineering & Technology (IJSRET), ISSN 2278 – 0882 Volume 6, Issue 5, 2017.

[2].InshirahRossan, MaleikaHeenaye, “Impact of Changing Parameters when Preprocessing Dorsal Hand Vein Pattern,” Procedia Computer Science 32 (2014) Elsevier, pp. 513 – 520, 2015.

[3].R. Raghavendra and J.Surbiryala, “Hand Dorsal Vein Recognition: Sensor, Algorithms and Evaluation,” IEEE, pp. 4799-8633, 2015.

[4].https://www.omicsonline.org/biometric-template-security-using-dorsal-hand-vein fuzzy-vault-2155-6180.1000145.php?aid=6684

[5].S. Zhao, Y. Wang, and Y. Wang, “Biometric verification by extracting hand vein patterns from low-quality images,” Proc. 4th ICIG, pp. 667–671, 2007.

[6].A. Kumar, K. VenkataPrathyusha, “Personal authentication using hand vein triangulation and knuckle shape,” IEEE Tran.Image Processing, Vol. 18, NO. 9, 2009.

[7].D. Huang, Y. Tang, Y. Wang, "Hand-Dorsa vein recognition by matching local features of multisource keypoints," IEEE Tran. Cybernetics, Vol. 45, 2015.

[8].M. Akram, H. Awan, Abdullah A. Khan, "Dorsal hand veins based person identification," IEEE Tran.Image Proc. Theory, Tools and App, 2014.

[9].T. Kumar, K. Premalatha, and A.M. Natarajan, "Hand vein pattern recognition using natural image statistics," Defence Science Journal, Vol. 65, pp. 150-158, 2015.

[10].Sheetal, R. P. Goela, K. Garg, "Image processing in hand vein pattern recognition system," IJARCSSE, vol. 4, pp 427-430, 2014.

[11].V. Brindha, "Biometric template security using dorsal hand vein fuzzy vault," Biometrics & Biostatistics, vol. 3, 2012.

[12].NishaCharaya, Priti Singh, "Human Authentication Based On Dorsal Hand Veins: A Review," International Journal of Pure and Applied Mathematics Volume 119 No. 16 2018, 2175-2185, 2017.

[13].Jiaojio Yan, Lanxiang Chong, and Ting Li, "A Method of Dorsal Hand Vein Authentication," Proc. SPIE 10806, Tenth International Conference on Digital Image Processing (ICDIP 2018), 108065Q (9 August 2018), doi:10.1117/12.2503, 2018.