A new wrist vein biometric system

Article · January 2015

DOI: 10.1109/CIBIM.2014.7015445

4 authors, including:

Abhijit Das
University of Southern California

Umapada Pal
Indian Statistical Institute

Miguel A. Ferrer
Universidad de Las Palmas de Gran Canaria

A New Wrist Vein Biometric System

Abhijit Das[a], Umapada Pal[b], Miguel Angel Ferrer Ballester[c] and Michael Blumenstein[a]
[a] Institute for Integrated and Intelligent Systems, Griffith University, Queensland, Australia
Email: abhijit.das@griffithuni.edu.au, m.blumenstein@griffith.edu.au
[b] Computer Vision and Pattern Recognition Unit, Indian Statistical Institute, Kolkata, India, Email: umapada@isical.ac.in
[c] IDeTIC, University of Las Palmas de Gran Canaria, Las Palmas, Spain, Email: mferrer@dsc.ulpgc.es

Abstract—**In this piece of work a wrist vein pattern recognition and verification system is proposed. Here the wrist vein images from the PUT database are used which were acquired in visible spectrum. As the provided image only highlights the vein pattern area so, segmentation was not required. Since the wrist's veins are not prominent, image enhancement was performed. An Adaptive Histogram Equalization and Discrete Meyer Wavelet were used to enhance the vessel patterns. For feature extraction, the vein pattern is characterized with Dense Local Binary Pattern (D-LBP). D-LBP patch descriptors of each training image are used to form a bag of features, which was used to produce the training model. Support Vector Machines (SVMs) were used for classification. An encouraging Equal Error Rate (EER) of 1.71% was achieved in our experiments.**

Keywords—Biometric; Vein Patterns; D-LBP; SVM; Bag of features, Adaptive Histogram Equalization; Discrete Meyer Wavelet.

I. INTRODUCTION

Biometrics is a field of study, for identifying individuals based on their psychological and, or behavioural characteristics. A reason of which it is the most promising technique for the personal identification of an individual. Biometrics has enjoyed a lot of encouragement for the last few decades by researchers from industries, academia and government. Various biometric techniques have been proposed in literature. Among them iris [1, 2], face [3] and finger print [4] are the most efficient and promising in the literature of biometrics.

Despite of a huge research each every biometric system has its own limitation in its ground of application. In order to increase its range of applications and constrains with respect to environmental condition multimodal biometrics was proposed in the late 20^{th} century. Various multimodal biometric systems have been proposed in the literature, still there is a further scope of research on biometric traits combining the different modal of biometrics.

In the literature it is found that, existing and popular biometrics system like iris etc., can be combine with some other surrounding biometric traits are really helpful and encouraging with respect to user cooperation and most likely it also negate the above mention limitation of biometric applicability. As a reason of which biometrics that are combined with the some existing biometric for example sclera [5, 6, 7, 8, 18] are becoming popular in literature nowadays. Due to above mention scenario the research on new upcoming biometric is required to be investigated independently before combining them in multimodal mode to assess the biometric applicability of such multimodal biometric system.

One such possible and promising upcoming biometrics can be the wrist vein pattern, which can be easily combine with finger print or palm print biometrics to make it more universal.

In the literature few works on wrist can be found [9, 10, 11, 19, 21, 22, 23 and 24]. In [24] first comes us with the proposal that the wrist vein can be utilized for biometric authentication.

In [23] the author proposed a dataset of wrist vein in infra-red band of 30 individual and proposed a prototype of for image capturing of wrist vein images by quality measurement. The first work on the wrist vein biometrics system can be found in [9], where a large dataset is used to report the result. Here low quality PUT vein images were used for biometrics. Binarization was used for enhancement further followed by correlation for recognition.

In [10] an analysis of the different segmentation technique is performed. For the segmentation analysis purpose enhancement was performed by Discrete Fourier Transformation and classification by correlation. In [11] benchmarking of the PUT dataset was reported. For enhancement Gaussian filter was used.

In [22] minutia feature based wrist vein recognition system was proposed. In [20] chain code based fusion is used for wrist vein recognition. In this work different level of skeleton fusion is used followed by chain code. In [19] spectral minutia based feature extraction was used to represent the wrist vein pattern after preprocessing the vein images. An approach to extract the vein minutiae and to transform them into a fixed-length, translation and scale invariant representation where rotations can be easily compensated is presented in [21].

To date, this biometric has not been prominently studied and very little is known about its usefulness. As reason in this work we have concentrated to explore this very new biometric trait.

This present work proposes a whole biometric system for personal identification based on wrist veins. Here wrist vein segmentation was not required as they were only prominent region in the images.

A new preprocessing approach for vein highlighting is proposed here by the Adaptive Histogram Equalization and Discrete Meyer wavelet. Wrist feature extraction based on the Dense Local Binary Pattern (D-LBP) is also new in the literature.

Support Vector Machines (SVMs) are used for classification.

The organization of the rest of the paper is as follows. Section II explains the proposed wrist vein enhancement process, feature extraction and classification. In Section III, the experimental details are described and Section IV draws the overall conclusions.

II. Proposed Approach

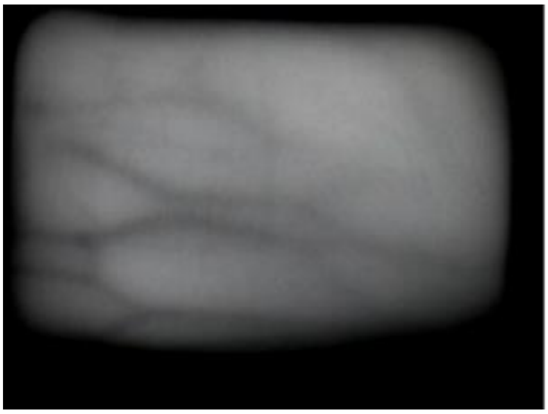
In this section, the proposed vein enhancement technique and feature extraction of wrist vein texture patterns are explained, and this is finally followed by the classification technique.

A. Wrist Vain Enhancement

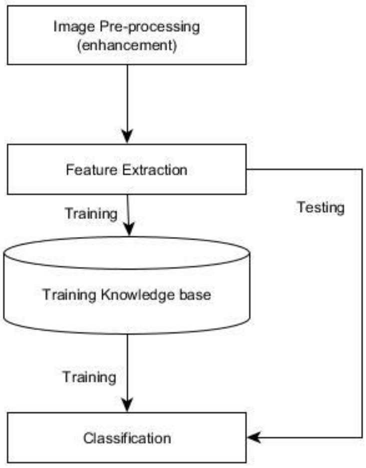
The wrist veins are not prominent clearly biometric applicability as shown in figure 1(a), so pre-processing is required. A system design of the proposed system is in figure 1(b).

At first an image pre-processing is done by a two stage image enhancement, followed a chain of feature extraction process. In the feature chain at first patch based feature extraction is performed to extract the texture properties of the vein pattern followed by feature clustering and at last spatial analysis of the feature to get the local and the global information in the different spatial plane of the feature.

For classification different kernel tricks of SVM (Support Vector Machine) is used to analysis the best classification result for the proposed system.



(a)



(b)

Figure 1: (a) A wrist vein image. (b) A system design of the proposed system.

In order to make them clearly visible, image enhancement is required. Adaptive histogram equalization [15] was performed with a window size of 14 x 14 (the window value was selected by analysis, window value that produces the best result was use for experimentation) was performed on the image to make the vein structure more prominent as shown in Figure 2.

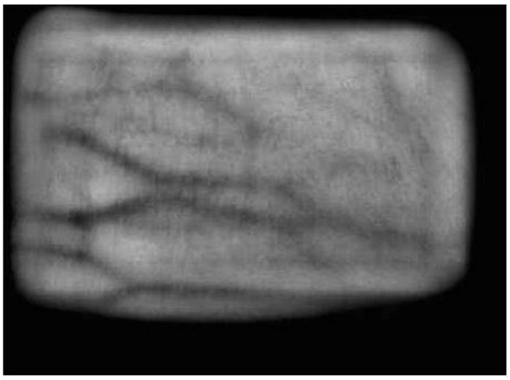


Figure 2: Image after adaptive histogram equalization

Further more, the Discrete Meyer wavelet [16] was used to enhance the vein patterns. A low pass reconstruction of the above-mentioned filter was used to enhance the image. Figure 3 shows the vein enhanced image after applying the filter.

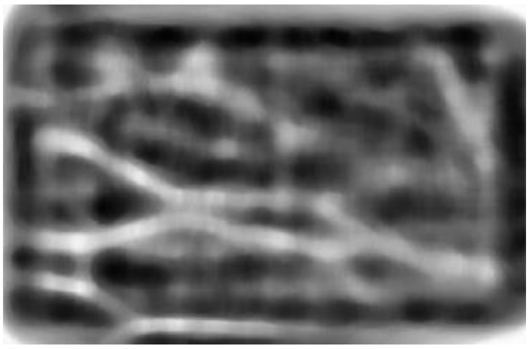


Figure 3: The final vein enhanced image.

B. Feature Eextraction Methodology

For feature extraction a local descriptor method was applied in this paper for the wrist vein feature. Feature extraction based on the Dense Local Binary Pattern (D-LBP) was performed here. A grid based local descriptor is used here as the vain patterns are better expressed in local feature than that of global feature. To include the global influence of the pattern latter SPM was used.

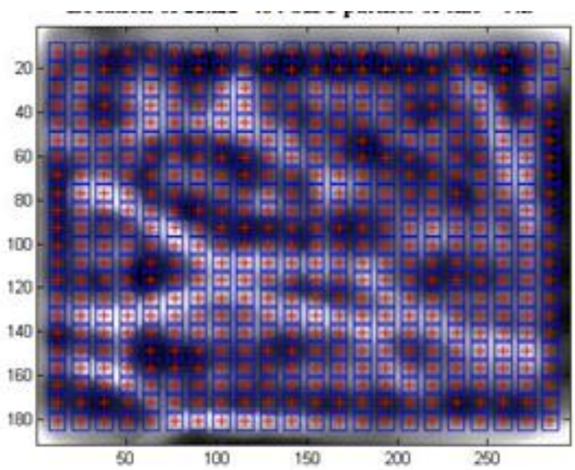
The LBP [12] operator labels the pixels of an image by thresholding the 3×3 neighborhood of each pixel and concatenating the results binomially to form a number. Assume that a given image is defined as $I(Z) = I(x, y)$. The LBP operator transforms the input image to $LBP(Z)$ as follows:

$$LBP(Z_c) = \sum_{p=0}^{7} s\left(I(Z_p) - I(Z_c)\right) \cdot 2^p,$$

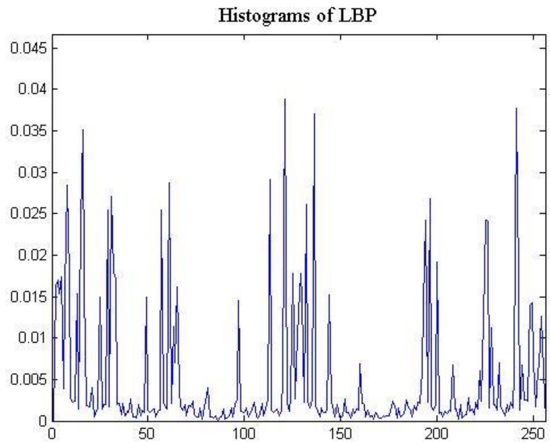
where $s(l) = \begin{cases} 1 & l \geq 0 \\ 0 & l < 0 \end{cases}$ is the unit step function and

$I(Z_p)$ is the 8-neighborhood around $I(Z_c)$.

D-LBP patch descriptors of each training image are used to form a bag of features, to produce the training model. For extracting the patch descriptors of each image was divided into four bins and eight orientations with 22x22 (the window value was selected by analysis, window value that produces the best result was use for experimentation) locations of 9x9 patch sizes (the patch value was selected by analysis, window value that produces the best result was use for experimentation). Next, a histogram of bin size 256, for each of these patches is calculated. Finally the histograms of each patch were calculated and then concatenated column wise to get the final descriptor.The histogram of the LBP patches is given in figure 4 (b) and the patch division of the image is given in figure 4(a).Descriptors from each of the training images are used to form a bag of features, which was used to produce the training model.



(a)



(b)

Figure 4: (a) The patch division of the image (b) Histogram of the D-LBP patches.

Next, a K-means clustering technique was applied on the patches on the training set for the generation of a codebook. The vocabulary size for the experiment was 1024. Descriptors from each training image are used with the code book to form a bag of features, farther which was used to produce the training model.

The BoF histograms are computed within each of the 2^i label segments of each patch K-means cluster, and all the histograms are finally merged to form a vector representation of the image by a spatial pyramid matching technique. Spatial pyramid matching is an extended version of the bag-of-features (BoF) model; it is simple and computationally efficient also. In the BoF model, the spatial order of local descriptors was not considered, so as a reason it restricts the descriptive power of the image representation.

The limitation of the BoF was mitigated in the SPM (Spatial Pyramid Matching) [13] approach, which was successfully applied on image recognition tasks. An image was partitioned into $2^i x\ 2^i$ segments where i = 0; 1; 2, represents different resolutions. The SPM reduces to BoF when the value of the scale $i = 0$.

Here, pyramid matching was performed in two-dimensional image space and uses a traditional clustering technique in feature space. The number of matches at level i was given by the histogram intersection function:

$$I\,(g(X);g(Y)) = \sum_{k=i}^{n} min\,(g_X(i); g_Y\,(i)) \tag{1}$$

Finally, the representation of the image for classification was the total number of matches from all the histograms, which was given by the definition of a pyramid match kernel:

$$K(X;\,Y) = \sum_{i=1}^{l} 0.5^{i}\,(I_i\ - I_{i-1}) \tag{2}$$

All (a total of 21 = 16+4+1) BoF histograms were computed from these three levels, and all the histograms were concatenated to get the final vector representation of an image. The equation below represents the pyramid match kernel for three scales:

$$K_\Delta = I_2 + 0.5(I_1 - I_2) + 0.25(I_0 - I_1) \tag{3}$$

C. *Classification*

Support Vector Machines (SVMs) [17] are used for classification in this work. SVMs area popular supervised machine learning technique, which perform an implicit mapping into a higher dimensional feature space. After the mapping is performed, it finds a linear separating hyper plane with maximal margins to separate data from this higher dimensional space.

The Library for Support Vector Machines (LIBSVM) was used here for the SVM implementation. Though various new kernels are being proposed, the most frequently used kernel functions are linear, polynomial, and Radial Basis Function (RBF). This work uses the RBF kernel.

SVM or LIB-SVM makes binary decisions and multi-class classification for personal identification. It has been performed in this study by adopting the one-against all techniques. We carried out grid-search on the hyper-parameters with 5-fold cross validation for selecting the parameters of the training sequence. The parameter settings that produce the best cross-validation accuracy were selected for our experiment.

To make a compares of the classifier other SVM kernel like Pegasus and Liner were also employed here. However best result was obtained in the RBF kernel.

III. Experimental Results

The experimental setup and the results of our proposed work are explained in this section.

A. Data Set

In order to evaluate the performance of the proposed method, the PUT wrist Vein database [14] was utilized for our experiments. A framework of the image capturing technique is given in figure 5 (g).

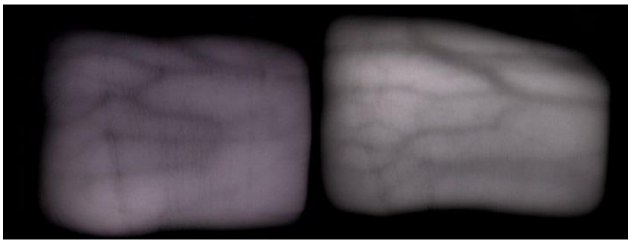
This database consists of 1200 RGB images taken in three distinct sessions (400 images in each session) from 50 identities (both left and right hand) where each channel of RGB color space is represented in grey-scale. In each session 4 images of each individual wrist vein are captured.

This database also consists of 1200 RGB palm vein images taken in three distinct sessions (400 images in each session) from 50 identities (both left and right hand) where each channel of RGB color space is represented in grey-scale. In each session 4 images of individual palm veins are captured.

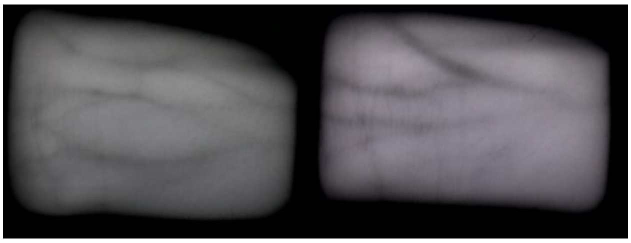
The database contains blurred images also. High resolution images (1024 x 768) are provided in the database. All the images are acquired in the Infra-red spectrum. All the images are in BMP format.

We have used different quality wrist vein images and some of the sample images are shown below in Figure 5(a-f).

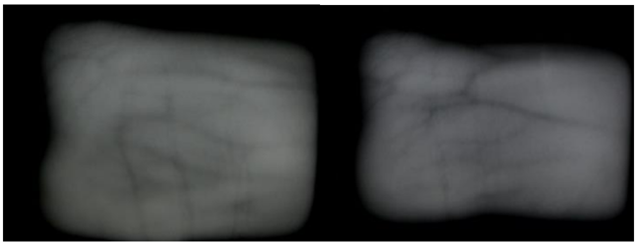
The dataset also consist of palm vein images they are not use in our experiment. Example of such images is in figure 5(h-m).



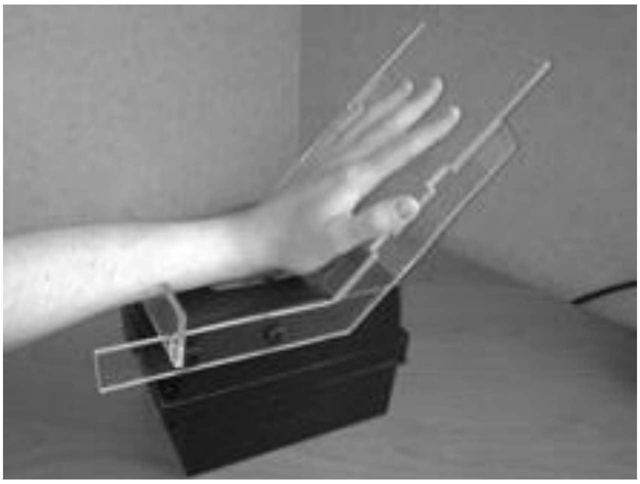
(a) (b)



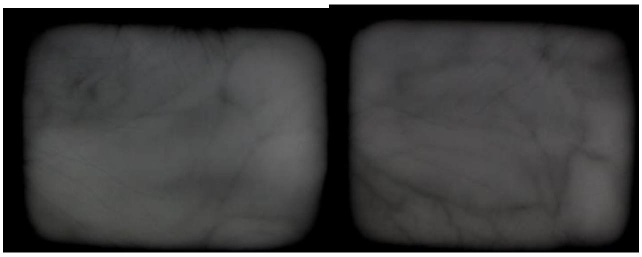
(c) (d)



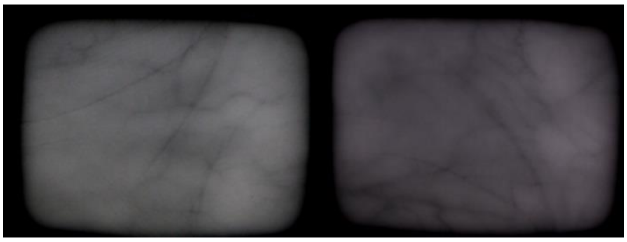
(e) (f)



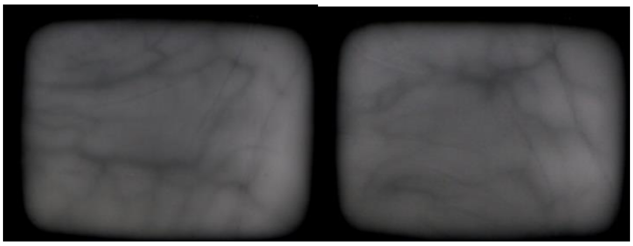
(g)



(h) (i)



(j) (k)



(l) (m)

Figure 5:(a)- (f) Different quality of palm vein images used in the experiments, (g) A framework of the image capturing technique[9].(h)-(m)Images of low resolution palm print from the mention dataset.

Only the wrist vein images are utilized in this experiment. Some of wrist vein images are having good quality of vein regions visibility, some of them are of medium quality and the third type was of poor quality with respect to vein visibility.

In the experiments, all the images of sessions 1, 2 and 3 were considered. Here single sessions as well as multi-session experiments were performed.

For the single session experiments, sessions 1, 2 and 3were considered separately, 2 images from each class of each session randomly chosen and utilized for training and the remaining 2 images for testing the performance.

For multisession experiment 4 images from session 1, they were considered for training, and session 2 for testing and vice versa. Similarly in other multisession experiment 4 images from session 2, they were considered for training, and session 3 for testing and vice versa.

Likewise 4 images from session 1, they were considered for training, and session 3 for testing and vice versa. We also tested by two session and training by one session and testing by two sessions and vice versa with all the possible combinations.

For single session experiments 100*2 (100 as because 50 individual left and right hand both and for each individual left and right hand pattern varies)scores for FRR and 100*99 score for FAR statistics.

For multisession with two sessions and 100*4 scores for FRR and 100*99 score for FAR statistics for multisession experiment between two sessions.

For multisession experiment between three session, when two for testing and one for training 100*8 scores for FRR and 100*99 score for FAR statistics are achieved. For multisession experiment between three session, when one for testing and two for training 100*4 scores for FRR and 100*99 score for FAR statistics are achieved.

All the simulation experiments performed here were developed in Matlab 2013a on the Windows 7 platform, core I5 processor having 4 GB of RAM.

B. Results for Wrist Vein Enhancement

Experimental results of the different enhancement techniques used for wrist vessel enhancement are discussed in this sub-section

a. Preprocessing by Adaptive Histogram Equalization

At first adaptive histogram equalization was performed with a tiled window size of 14x 14 at a clip limit of 0.01, with a full range and distribution exponential to get the best result.

b. Preprocessing by Adaptive Wavelet Filter

Furthermore, the Discrete Meyer wavelet was used to enhance the vessel patterns more prominently. Low pass reconstruction with a cut off range of -0.9 * e^{10} and a window size of 3x3.

c. Preprocessing by Adaptive Histogram Equalization

Next, the adaptive histogram equalization with a tiled window size of 14x 14 at a clip limit of 0.01is used again, with full range and distribution exponential is applied to the filtered image.

C. Experimental result of the multisession and single sessions experiment

The result obtained from the different multisession and single session experiments performed are in the table 1.

It can be observed from the above experiment that result did not varied between the experiments carried out with Single session and multisession experiment with two training session and one testing session.

This signifies the robustness of the system with variation in time duration and other environmental conditions.

Whereas the result for the multisession experiment with one session for training and two session for testing have deteriorated a bit, possible reason can be the ratio of training and testing which is low for this instances (4 images for training and 8 images for testing).

TABLE I. EQUAL ERROR RATE OF THE MULTISESSION AND SINGLE SESSION EXPERIMENTS PERFORMED

Type of experiment	EER in %
Single session using session 1	**0.8**
Single session using session 2	**0.83**
Single session using session 3	**0.75**
Multi session using session 1 as test 2 as train	**0.91**
Multi session using session 2 as test 1 as train	**0.89**
Multi session using session 1 as test 3 as train	**0.88**
Multi session using session 3 as test 1 as train	**0.89**
Multi session using session 2 as test 3 as train	**0.81**
Multi session using session 3 as test 2 as train	**0.84**
Multi session using session 1 as test 2 and 3 as train	**0.81**
Multi session using session 2 as test 1 and 3 as train	**0.8**
Multi session using session 3 as test 2 and 3 as train	**0.79**
Multi session using session 1 and 2 as test and 3 as train	**1.31**
Multi session using session 1 and 3 as test and 2as train	**1.42**
Multi session using session 3 and 2 as test and 1as train	**1,23**

D. Classifier Selection

For classification, SVMs are used as previously indicated in the proposed methodology section. Three types of SVMs are used here, namely the RBF kernel, Pegasus and Linear.

It can be inferred from the below table that the SVM library with the RBF kernel produces the best results for the proposed experiment.

TABLE II. EQUAL ERROR RATE OF THE DIFFERENT SVMS USED FOR CLASSIFICATION

Classifier	**Equal Error Rate (%)**			
	Multisession Best result	***Single session 1***	***Single session 2***	***Single session 3***
Lib SVM	0.79	0.8	0.83	0.75
Pegasus	1.97	1.9	1.82	1.82
Linear	2.37	0.97	0.98	0.98

E. Time complexity

The average time complexity of vessel enhancement, feature extraction and classification are given below in Table III. It can be inferred from the below table that the time complexity of the proposed technique was satisfactory.

All the simulated data reported here were developed in Matlab under the Intel I5 processor in the Windows environment.

TABLE III. TIME COMPLEXITY TABLE

Different Steps in the proposed wrist biometric system	***Time in Seconds***
Vessel enhancement	0.21
Feature extraction	0.311
Classification	0.25

F. Overall Experimental Results

The overall experimental results are summarized below in Table IV.

TABLE IV. EQUAL ERROR RATE OF THE OVERALL RESULT USING THE DENSE LBP FEATURE BEST RESULT OF EACH SESSION EXPERIMENT

Feature	**Equal Error Rate (%)**		
	Multisession With three session	***Multisession With two session***	***Single session***
Dense **LBP**	0.79	0.81	0.75

Multisession experiment for session 1and 2 for training, and session 3 as testing, produces the best result for the multi-session experimental environment.

For the single session experiments, session 3 produces the best results. It can also be concluded from the above table that the result for the multisession experiments have deteriorated somewhat. The possible cause can be the presence of some lighting and other conditions changes in between the sessions.

Below is the ROC (Receiver Operating Characteristic) curve for the best multi-session experiment. On the Y axis we have the genuine acceptance rate and the X axis represents the false acceptance rate. The graph depicts that a recognition accuracy of 99.21% was achieved for the multi-session experiments.

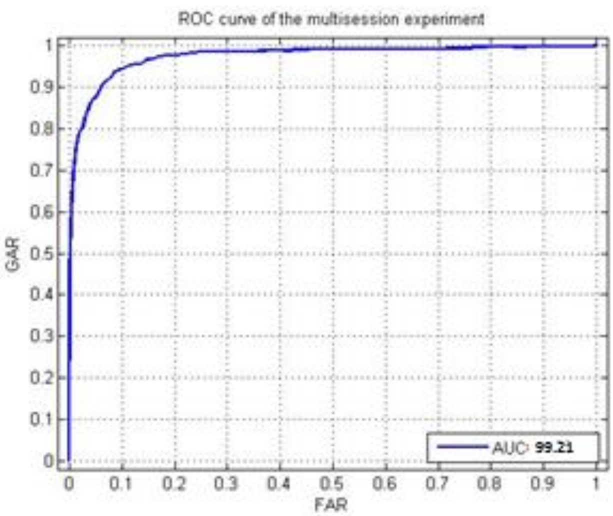


Figure 6: ROC curve of the multisession experiment

G. *Comparison with the state-of-the-art*

The results of the proposed work are analysed with respect to the state-of-the-art by comparing it with the most similar work on the PUT hand vein dataset that could be found in the literature. Table V reflects a state-of-the-art comparative analysis of the most similar work on the PUT hand vein dataset.

The proposed technique outperformed the other previous techniques in terms of recognition and validation which is reflected in the table below. Also the result reported in the previous works was not reported with multisession experiment.

Hence the proposed scheme is the most realistic one, since it did not discarded any images from the dataset used, and the experiments was also performed with multisession data, where the sessions have variation in change in environmental condition, population, data accruing technique and time span gap.

Another significant novelty of this work is, the usage of statistical classifier like SVM in contrast to the other related work, where correlation matching was used for classification.

In order make a state of art compares with the most similar work that can be found in the literature on PUT dataset are compares with the different enhancement, feature extraction and classification used in the previous work with contrast the proposed in the table VI

TABLE V. A STATE OF THE ART COMPARISON OF OTHER PIECES OF WORK ON PUT DATASET

Work	***Equal Error Rate (in %)***
Kabaciński et al. [9]	3.51
Kabaciński et al. [10]	2.19
Kabaciński et al. [11]	3.8
Proposed System	0.79 (multisession experiment with all the images)

TABLE VI. A STATE OF THE ART COMPARISON OF OTHER PIECES OF WORK ON DIFFERENT STEPS ON PUT DATASET

Work	***Enhancement technique***	***Feature extraction technique***	***Classification technique***
Kabaciński et al. [9]	Binarization	Correlation Matching	
Kabaciński et al. [10]	Discrete Fourier Transformation	Correlation Matching	
Kabaciński et al. et al. [11]	Gauss filters	Correlation Matching	
Proposed System	Adaptive histogram equalization and a low pass Discrete Meyer Wavelet	Dense LBP	SVM

IV. CONCLUSIONS

This paper has proposed a novel method of wrist vein recognition. Adaptive histogram equalization were used for wrist vein preprocessing and a low pass Discrete Meyer Wavelet reconstruction filter for establishing appropriate features was employed. Dense LBP is used here for feature extraction, which provides information about the different pattern structures followed by clustering by K-means. Identification is achieved by SVM classification. The proposed approach has achieved high recognition accuracy employing the PUT hand vein dataset.

Future scope will include exploring the multimodal biometric system using all biometric trait present in hand.

REFERENCES

[1] A. Das and R. Parekh, Iris Recognition using a Scalar based Template in Eigen-space, International Journal of Computer Science and Telecommunication, 3(5), 74-79.May 2012.

[2] A. Das and R. Parekh, Iris Recognition in 2D Eigen-space, International Journal of Computer Applications, 52(19), 1-6, 2012.

[3] A. Das, Face Recognition in reduced Eigen plane", International Conference on Communications, Devices and Intelligent Systems, 620- 623, 2012.

[4] D. Maltoni, Handbook of Fingerprint Recognition, Springer, New York, 2003.

[5] A. Das, U. Pal, M. F. A. Ballester and, M. Blumenstein, A New Method for Sclera Vessel Recognition using OLBP, In Proc. Chinese Conference on Biometric Recognition ,LNCS 8232, 370–377,2013.

[6] M. A. F. Ballester, A. Morales, A. Das, M. Blumenstein and U. Pal, Model based Sclera vessels segmentation with SIFT Recognition and its combination with Iris", appeared in Spanish biometric consodium, VII Jornadas de Reconocimiento Biometrico de Personas, 68-76, 2013.

[7] A. Das, U. Pal, M. F. A. Ballester and, M. Blumenstein, ScleraRecognition Using D-SIFT, In Proc. 13th InternationalConference on Intelligent Systems Design and Applications, 74-79, 2013.

[8] A. Das, U. Pal, M. Blumenstein and M. F. A. Ballester, Sclera Recognition - A Survey, In Proc. Recent Advancement in Computer Vision and Pattern Recognition, 917-921, 2013.

[9] R. Kabaciński and M. Kowalski. Human vein pattern segmentation from low quality images a comparison of methods. Image Processing and Communications Challenges 2, 84 of Advances in Intelligent and Soft Computing, 105-112, 2010.

[10] R. Kabaciński and M. Kowalski.Human vein pattern correlation - a comparison of segmentation methods.Computer Recognition Systems 4, 95 of Advances in Intelligent and Soft Computing, 51-59, 2011.

[11] RafałKabaciński and Mateusz Kowalski.Vein pattern database and benchmark results. Electronics Letters, 47(20), 1127-1128, 2011.

[12] T. Mäenpää, M. Pietikäinen, Texture Analysis with local binary Patterns, Handbook of Pattern Recognition and Computer Vision, 3rd edn. World Scientific, 197-216, 2005.

[13] S. Lazebnik, C. Schmid, and J. Ponce, "Beyond bags of features: Spatial pyramid matching for recognizing natural scene categories," In Proc. Computer Vision and Pattern Recognition (CVPR), 2, 2169–2178, 2006.

[14] PUT vein dataset available at http://biometrics.put.poznan.pl/home/new-news-page/

[15] S. M. Pizer, E. P. Amburn and J. D. Austin, Adaptive Histogram Equalization and Its Variations, Computer Vision, Graphics, and Image Processing 39: 355-368, 1987.

[16] I. Daubechies, *Ten lectures on wavelets*, CBMS-NSF conference series in applied mathematics, SIAM Ed: 117–119, 1992.

[17] H. William, A. Saul, T. William, B. P. Flannery, Support Vector Machines. Numerical Recipes: The Art of Scientific Computing (3rd ed.). New York: Cambridge University Press. ISBN 978-0-521-88068-8, 2007.

[18] A. Das, U. Pal, M. F. Ballester and M. Blumenstein, Fuzzy Logic Based Sclera Recognition, In WCCI: 561-568, 2014.

[19] D. Hartung, M. A. Olsen, H. Xu, and C. Busch, Spectral minutiae for vein pattern recognition. In Biometrics (IJCB), 2011 International Joint Conference on, 1 –7, 2011.

[20] D. Hartung, A. Pflug, and C. Busch, Vein pattern recognition using chain codes spatial information and skeleton fusing .In Sicherheit , 245–256, 2012.

[21] D. Hartung, M. A. Olsen, H. Xu, H. T. Nguyen and C. Busch, Comprehensive analysis of spectral minutiae for vein pattern recognition. In IET Biometrics (1), 25–36, 2012.

[22] J. Uriarte-Antonio, D. Hartung, J. Pascual and R. Sanchez-Reillo, Vascular biometrics based on a minutiae extraction approach. In Security Technology (ICCST), IEEE International Carnahan Conference on , 1 –7, 2011.

[23] M. Akhloufi . and A. Bendada, Capturing Hand or Wrist Vein Images for Biometric Authentication Using Low-Cost Devices, Sixth International Conference on Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP), 318 – 322, 2010

[24] J.E. Suarez Pascual, ; J. Uriarte-Antonio, R. Sanchez-Reillo, M.G. Lorenz, . Hand and Wrist Physiological Features Extraction for near Infrared Biometrics, Canadian Conference on Computer and Robot Vision, CRV '08. 341 – 344, 2008.