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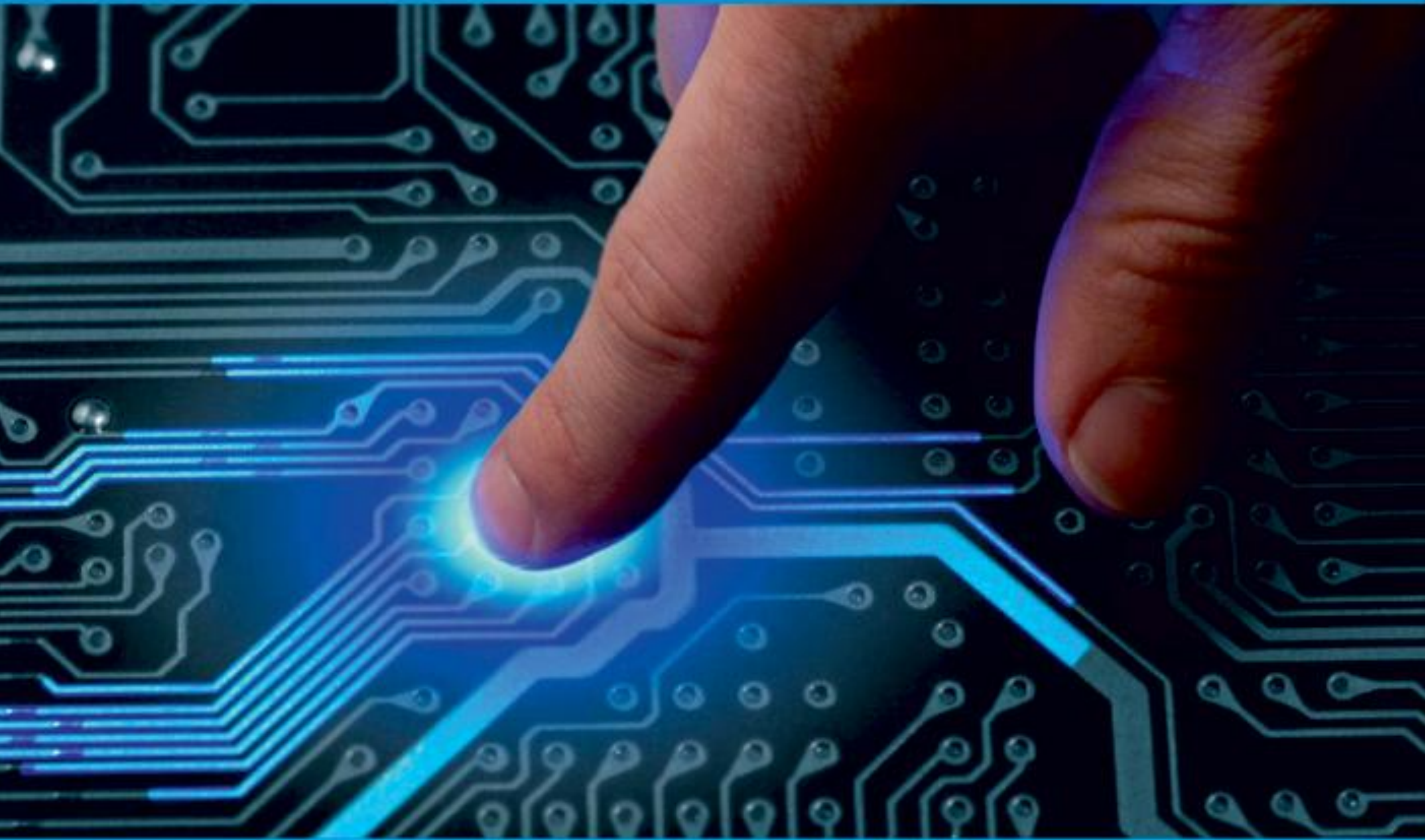

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Vein Biometric System Using Local Binary Pattern for Personal Authentication System

N. Manikanta Reddy, K. Srikanth, K. Rajesh, K. Sukhesh

UG Students, Department of Electronics and Communications Engineering, Vasireddy Venkatadri Institute of Technology, Nambur, Guntur, AP, India

ABSTRACT: This work explores the field of finger vein recognition – the identification of individuals using the unique vein patterns of their fingers. Automated personal authentication is becoming increasing important in modern society, and is often used to control access to facilities and personal financial information. Biometrics, the science of identifying individuals based on personal characteristics, has the advantage that subjects can be recognized according to their personal attributes as opposed to what they remember (password) or possess (identification card). Although fingerprinting is currently the most mature biometric technology today, vein patterns boast a number of advantages including the facts that they cannot be forged and are not affected by changes to the surface of the skin.
However, the existing biometric systems are highly complex in terms of time or space or both, and thus not suitable in very high security. Thus, an embedded finger-vein recognition system for authentication is proposed. The system is to be implemented using novel finger vein recognition algorithm and lacunae, fractal dimension and LBP algorithms used for feature extraction and the matching of the extracted feature is done using the distance classifier. The analysis is done using the various features from which the kurtosis, range shows large variation from person to person. Based on this analysis finger vein recognition becomes easier and reliable.

KEYWORDS: - LBP(local binary pattern),NN(Nearest neighbour),CLAHE(Contrast Limited Adaptive Histogram equalization)

INTRODUCTION

Personal identification is becoming increasingly important in modern society where automated systems are used to control access to facilities and personal financial information. Everyday examples include access control to buildings and internet banking. Biometrics, the science of identifying individuals based on personal attributes , has the advantage that subjects can be identified via personal characteristics as opposed to what they possess (an identification card) or what they may remember (a password).A novel and fairly recent biometric technique, is the identification of individuals based on the vascular patterns of their hands or fingers. This project develops a software classification system to identify an individual based on their unique finger vein patterns.

Table 1 Comparison of different biometric methods

Biometric	Security		Practicality			
	Anti-forgery	Accuracy	Speed	Enrolment	Convenience	Cost
Fingerprint	Poor	Average	Average	Poor	Average	Good
Iris	Average	Good	Average	Average	Poor	Poor
Face	Average	Poor	Average	Average	Good	Poor
Voice	Average	Poor	Average	Average	Good	Average
Finger Vein	Good	Good	Good	Average	Average	Average

Normally for any sort of machine learning / deep learning they are four stages that is dataset, pre-processing and what type of classifier used.

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DATASET

The SDUMLA-HMT (Shandong University Machine Learning and Applications) biometric database was used as a source of both training and testing data. The database consists of finger vein images of 106 individuals in addition to samples of other biometric modalities such as the iris and face. There are vein images of six fingers (three on each hand) and since vascular patterns differ on every finger of every hand, there are effectively $106 \times 6 = 636$ possible classes to identify. Furthermore, six images per class were captured resulting in a total of 3816 images. Each image is 320×240 pixels in dimension and stored in the uncompressed, “Bitmap” file format. The vein imaging device, shown in

PRE-PROCESSING: -

In order to extract the intersection points of veins, we first need to segment the veins from the rest of the image. The goal of this stage is to produce a binarized image where the foreground (white) pixels represent the actual vein and the

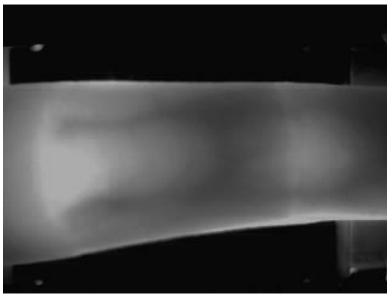

Fig 1:- **unprocessed vein pattern (right)**

background (black) pixels represent the remaining tissues of the finger.The extraction of the Region of Interest (ROI) and subsequent contrast enhancement using the CLAHE algorithm. Thereafter, the algorithms examined to segment the veins from the images are discussed.

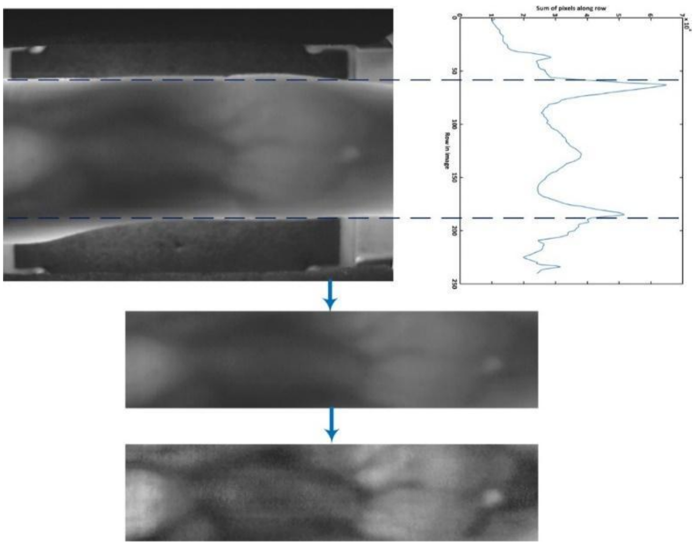

Fig 2: - **Flow diagram of pre-processing.**

This region was obtained by taking the illumination profile along the vertical axis (by summing all the pixels along the rows of the grayscale image) and retaining pixels along the middle 80 rows from the peaks of the profile. These peaks correspond to the boundary of the finger and scanning lens, which contains the brightest pixels (since brighter pixels have higher intensity values than darker ones). In general, the observed finger region is approximately 100 pixels wide. However, we use a conservative estimate of 80 pixels to account for variation in finger widths. Finally, we improve the contrast of the image using the CLAHE algorithm.

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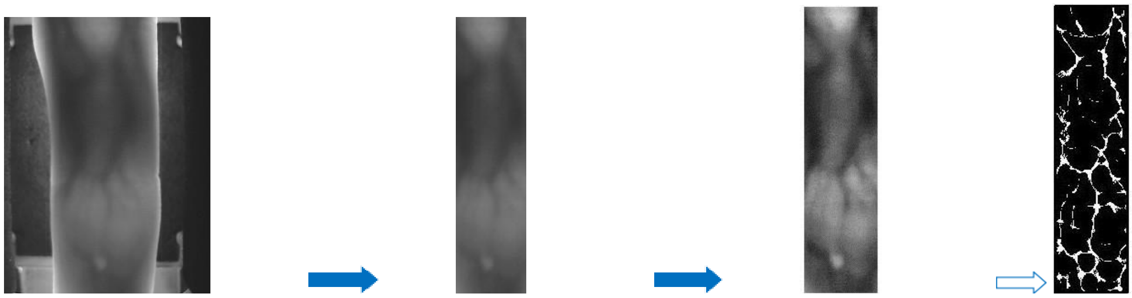
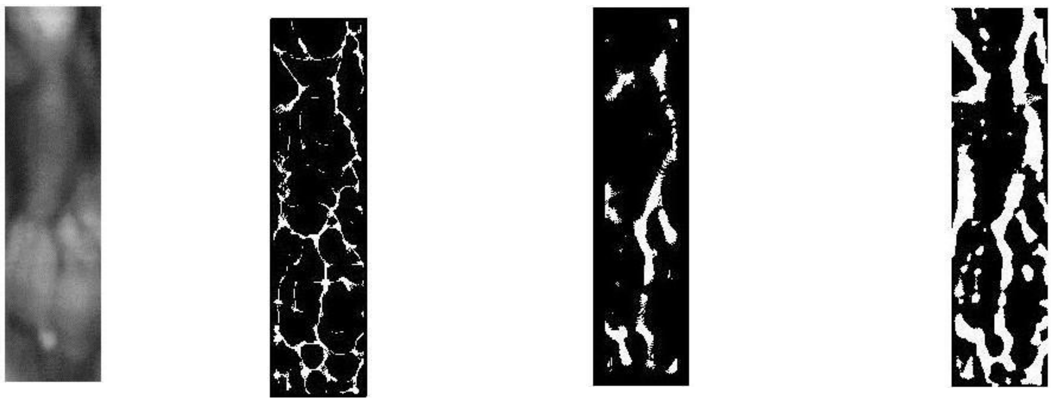


(a)Original image **(b) ROI Extractoin** **(c) Contrast enhancement** **(d)Vein segementation**

VEIN SEGMENTATION

The final, and most important stage of pre-processing is to extract the veins and create a binary, thresholded image. common thresholding techniques do not work due to the non-uniform illumination in vein images. Three vein segmentation algorithms were evaluated and one developed by the author (involving high-pass filtering).



Original image **Miura's Maximum Curvature Method** **Huang's wide line Detector** **Proposed method**

FEATURE EXTRACTION: -

The output of the pre-processing stage is a binary image where the white, foreground pixels represent the actual vein. In this section, we extract the positions of bifurcation points as our first set of features. Bifurcations are the points where one vein splits into two. Contrastingly, it can also be thought of as the points where two veins intersect. Bifurcations were considered to be reliable features and since the number and position of these points are unique among individuals. Fig shows the operations required to extract bifurcations, which are explained in the following subsections. We then show in section how these bifurcations can be clustered together to create a different set of features.

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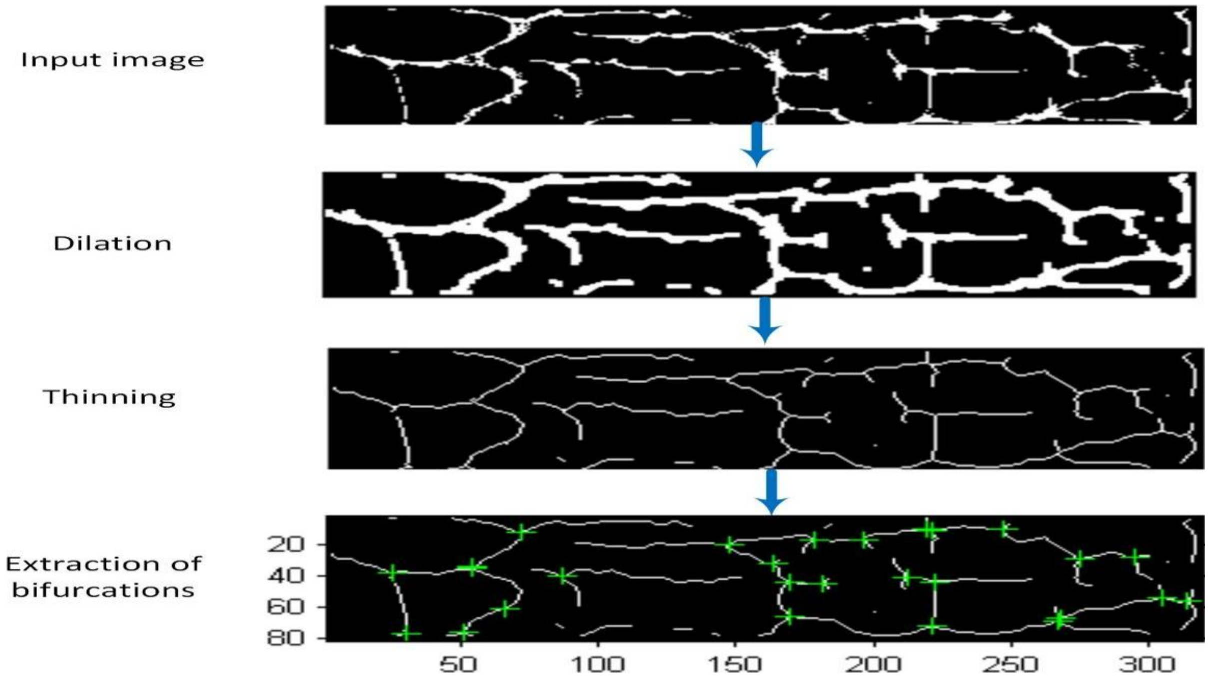
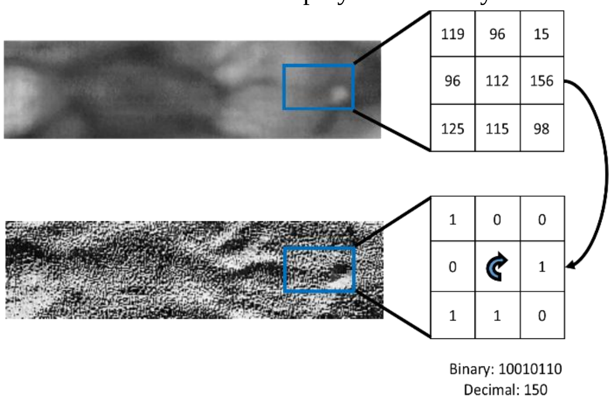


A recap of the $LBP_{8,1}$ descriptor applied to a vein image

Local Binary Patterns (LBP), are formed by thresholding the intensity value of a pixel to all of its neighbours. This process creates a binary pattern which can then be represented as a decimal number, as shown in Figure 4.2. It thus follows that the LBP Features obtained from the vein image will be of almost the same dimension as the input image (the pixels along the border of the image are excluded by LBP as they do not have sufficient neighbors). In our case, our regions of interest which have dimensions of 320 × 80 will produce LBP features of size 318 × 78.

CLASSIFICATION: -

Once again, we use a Nearest Neighbor (NN) algorithm to classify the various forms of LBP features extracted. The operation of the NN classifier is identical to the one we employed to classify minutiae- based features. However, since



we are working with different features, we also require different distance metrics to compare these features. In order to match Canonical LBP features, we use the Hamming Distance whilst for the histograms of Uniform LBP features, we use the Chi-Square distance. Finally, when we take the Fourier Transform of the histograms, we use the Euclidean Distance for template comparison. These distance functions are described in the following subsections.

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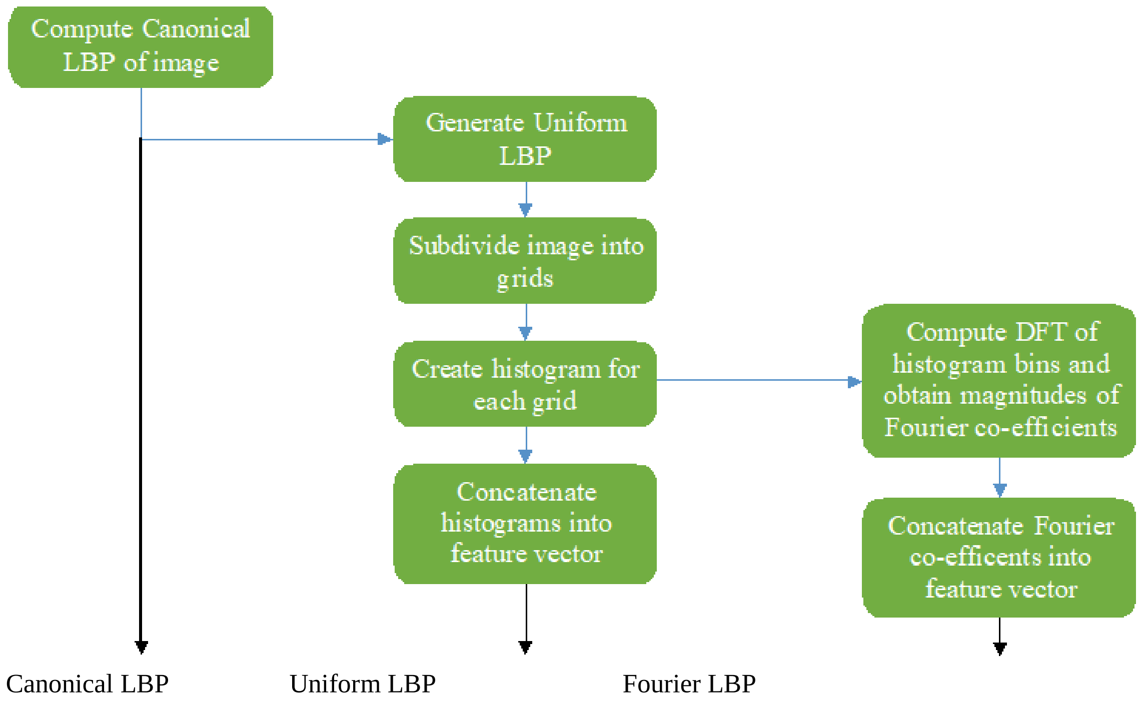

Flow diagram of the feature extraction process

Flow diagram showing the process of extracting various LBP-based features. Multiple stages are performed once and used for extracting different features

Comparison of developed LBP classifiers

	Canonical LBP	Uniform LBP	Fourier LBP
EER (%)	5.565	**1.518**	4.429
d^{j} (units)	4.538	**5.219**	4.965
Zero-FAR (%)	7.589	**2.530**	6.071
Minimum Average Error (%)	3.540	**1.260**	3.040
Total Identification Time (s)	1.284	1.194	**1.181**

The Uniform LBP Classifier was found to outperform Canonical LBP and Fourier LBP by quite a large margin as all of its error rates were significantly lower. Moreover, we can even argue that the Uniform LBP Classifier is superior to other identification systems from current literature which have been tested on a similar training database. Whilst the Uniform LBP Classifier was clearly the best, we should also remember that the Fourier LBP Classifier had an EER of 4.43% which still meets our project objective of an EER below 5%. However, one question still remains: Although we have developed various different identification systems in the last four chapters, is it possible to combine these together into a more powerful classifier.

The aim of this project was to ascertain whether vein recognition systems could be developed to reliably identify individuals. Therefore, this project can be considered a success as not only have we fulfilled our original objectives, but we have also made contributions to the domain of vein recognition. These two aspects, in addition to an overview of the Uniform LBP classifier which performed the best.

BEST CLASSIFIER

The Uniform LBP classifier is clearly the best choice as its EER of 1.52% is nearly half that of any other classifier. Moreover, its total identification time of 1.19 seconds is within our project target. A variant of this, the Raw Uniform LBP classifier, is able to reduce this time to 0.75 seconds by not segmenting the veins from the image before extracting features in the pre-processing stage of its pipeline. However, in order to attain this increased speed, the EER increases

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to 2.87%.
The decision of whether to opt for faster identification time or improved classification accuracy depends on the application. However, the author's opinion is that the 0.44 seconds saved by Raw Uniform LBP will barely be noticed by human users. As a result, the more accurate, standard Uniform LBP classifier is the best.

FINAL WORDS

Vein recognition is an effective technique for identifying individuals. Our best method, the Uniform LBP Classifier, achieved an Equal Error Rate (EER) of 1.52% and Zero-FAR of 2.53% which we can consider as state of the art. To place these error rates and recent advancements in biometric technologies in context, we draw attention to the Fingerprint Verification Competition held in 2004. The winning entry achieved an EER of 2.07% and Zero-FAR rate of 6.21%. While the databases and testing procedures may have been different, the fact that our vein identification system achieved better error rates than the best fingerprint matching algorithm ten years ago is significant. It confirms that biometric vein recognition shows immense promise as an accurate and convenient solution to modern society's problem of automated personal identification.

USED ALGORITHMS: -

CLAHE ALGORITHM for vein segmentation purpose and different types of LBP methods like uniform, canonical and Fourier classifier respective working algorithms of them.

FUTURE WORK AND RECOMMEND

DESIGN OF VEIN IMAGING HARDWARE

In this project, we used a database of existing finger vein images. The next step is to design and implement a finger vein imaging device. The vein scanner must be carefully designed such that the captured images do not suffer from non-uniform illumination (unlike the images from our SDUMLA- HMT database) since this hinders pre-processing and feature extraction operations.
The imaging hardware can then be combined with the classification software developed in this project to create a complete biometric authentication system which can be used in practical situations. In order to make a standalone system, the vein recognition software would also have to be implemented on a suitable embedded platform. It is almost certain that building a complete authentication system for commercial use will also produce many unexpected design challenges.

IMPROVED VEIN SEGMENTATION

All the identification systems developed in this project required the veins to be segmented from the image in the pre-processing stage of the biometric pipeline. We used Miura's Maximum Curvature algorithm to perform this segmentation and even though it was the best technique that we tested; it could be improved as it is susceptible to errors arising from non-uniform illumination. Although this advancement should lead to the accuracy of all the identification systems increasing, the minutiae-based classifiers (MHD and Cluster) should experience the greatest benefit. It may then be unnecessary to adjust our MHD distance function (using the *f* parameter) to compensate for segmentation noise.

APPLICATIONS

- Used for any sort of authentication purposes.
- Used at banking sector.
- At mobile systems and security-based systems.

CONCLUSION

Can't be easily forged and also gives highest version of authentication system. But this system price may be too high due to raw finger image extraction scanner, camera cost is high and algorithm working complicity will be high for high stored data and we need optimal classifier for classification purpose.

REFERENCES

[1] A. Jain, P. Flynn, and A. Ross, *Handbook of Biometrics*. Springer, 2007.
[2] K. Wang, M. Hui, O. Popoola, and J. Li, "Finger Vein Recognition," in *Biometrics* (J. Yang, ed.), pp. 29–53, InTech, 2011.

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[3] T. Yanagawa, S. Aoki, and T. Ohyama, "Human finger vein images are useful for personal identification human finger vein images are diverse and its patterns are useful for personal identification," *MHF Preprint Series*, vol. 12, pp. 1–12, Apr. 2007.

[4] Y. Lu, S. J. Xie, S. Yoon, Z. Wang, and D. S. Park, "An available database for the research of finger vein recognition," *2013 6th International Congress on Image and Signal Processing (CISP)*, pp. 410–415, Dec. 2013.

[5] A. Pflug, D. Hartung, and C. Busch, "Feature extraction from vein images using spatial information and chain codes," *Information Security Technical Report*, vol. 17, pp. 26–35, Feb. 2012.

[6] D. Maltoni, D. Maio, A. Jain, and S. Prabhakar, *Handbook of Fingerprint Recognition*. Springer Professional Computing, Springer, 2009.

[7] B. A. Rosdi, C. W. Shing, and S. A. Suandi, "Finger vein recognition using local line binary pattern.," *Sensors (Basel, Switzerland)*, vol. 11, pp. 11357–71, Jan. 2011.

[8] A. Djerouni, H. Hamada, A. Loukil, and N. Berrached, "Dorsal Hand Vein Image Contrast Enhancement Techniques," *International Journal of Computer Science Issues (IJCSI)*, vol. 11, no. 1, pp. 137–142, 2014.

[9] C. Wilson, *Vein Pattern Recognition: A Privacy-Enhancing Biometric*. Taylor & Francis, 2011.

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