ICCIT 2020

23rd INTERNATIONAL CONFERENCE ON
COMPUTER AND INFORMATION TECHNOLOGY

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Modified Maximum Curvature Method (MMCM) and Logistic Regression: A Hybrid Architecture for Finger Vein Biometric Recognition System

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INTRODUCTION

- Biometrics authentication is a method used to measure unique traits and behavioral characteristics of a user for identification.
- Finger Vein recognition uses the unique vein pattern of each individual.
- Images captured during image acquisition of finger vein shows fluctuation in quality.
- Modified Maximum Curvature Method (MMCM) is proposed for vein extraction from the images.
- Logistic Regression (LR) is proposed for classification.

MOTIVATION

- Security Concerns are at a rise
- Most Biometric modalities are affected easily by environmental factors or have complex hardwares.
- Finger vein has minimum possibility of duplication.
- Finger vein authentication is hygienic thus requires low hardware maintenance.
- Finger vein authentication has low False Acceptance and False Rejection Rate.
- The authentication system can be used for credit/debit authentication, banking, employee tracking, etc.

OBJECTIVE

- Finding the proper combination of image preprocessing and feature extraction to tackle illumination and dimension fluctuation observed in images captured with NIR.
- Determining which machine learning classification model performs best for classifying/identifying the users.

RELATED WORK

RELATED WORK

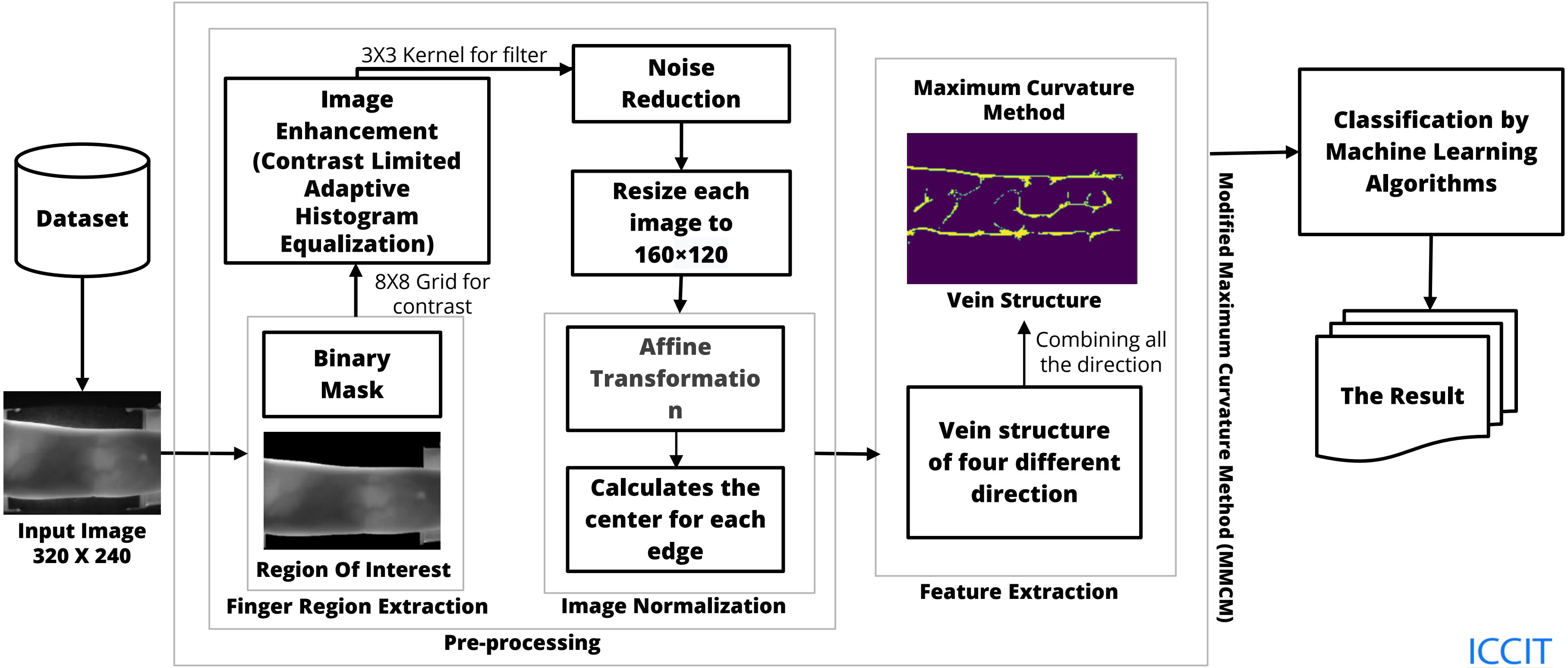
- **Miura et al. [1] - 2007**
  - **Finger Vein Extraction**: Maximum Curvature Method (MCM)
  - **Classifier:** Template Matching
- **Xie et al. [2] - 2014**
  - **Finger Vein Extraction**: Explicit Guided Directional Filter
  - **Classifier:** Extreme Learning Machine (ELM)
- **Kumar et al. [3] - 2015**
  - **Finger Vein Extraction**: Local Binary Pattern (LBP)
  - **Classifier:** Multi Support Vector Machine (MSVM)
- **Liu et al. [4] - 2016**
  - **Finger Vein Extraction**: Efficient Local Binary Pattern (ELBP)
  - **Classifier:** Random Forest

RELATED WORK (CONT.)

- **Jumaa et al. [5] - 2019**
  - **Finger Vein Extraction**: Hierarchical Centroid + Histogram of Gradients
  - **Classifier:** K-Nearest Neighbor (KNN)
- **Khanam et al. [6] - 2019**
  - **Finger Vein Extraction**: Frangi Filter + Features from Accelerated Segment Test (FAST) + Freak Descriptor Extraction
  - **Classifier:** KNN
- **Qayoom et al. [7] - 2019**
  - **Finger Vein Extraction**: Gabor filter + FAST + Freak Descriptor
  - **Classifier:** Naive Bayes + Discriminant Analysis
- **Meng et al. [8] - 2020**
  - **Finger Vein Extraction**: Pixel Level Feature Extraction
  - **Classifier:** SVM

PROPOSED METHOD

PROPOSED METHOD



PROPOSED METHOD (CONT.)

- **Step 1: Image Preprocessing**
  - **Finger Region Extraction**

Fig. 1.1: Binary Mask

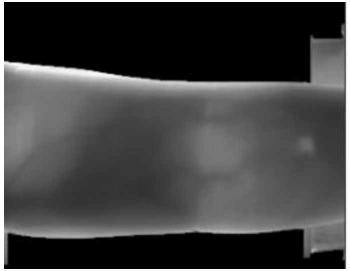


Fig. 1.2: Region Of Interest

  - **Image Enhancement:**
    - Contrast Limited Adaptive Histogram Equalisation (CLAHE)

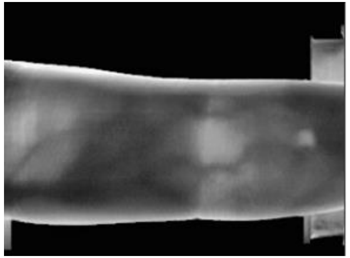


Fig. 1.3: Enhanced Image

PROPOSED METHOD (CONT.)

- **Noise Reduction:**
    - Gaussian Filter
- **Normalization:**
    - Affine Transform

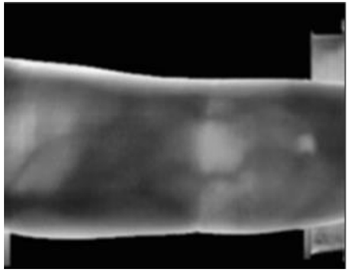


Fig. 2.1: Filtered Image

Fig. 2.2: Normalized Mask

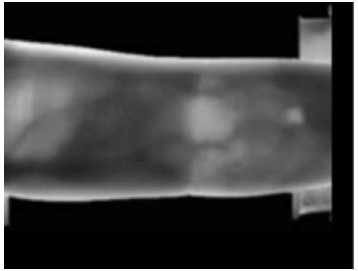


Fig. 2.3: Normalized Region Of Interest

PROPOSED METHOD (CONT.)

- **Step 2: Feature Extraction**
  - **Maximum Curvature Method (MCM)**
    - **Extraction of the center point of the veins**
      - Calculation of the curvature of profiles
      - Detection of the center of the veins
      - Assignment of scores to the center position
      - Calculation of all the profiles
    - **Connection of vein centers**
    - **Labelling the image**
      - Binarization

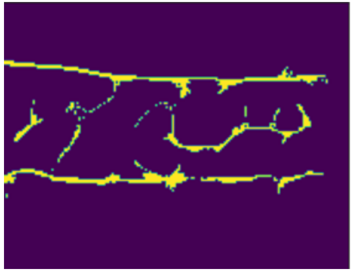


Fig. 3.1: Extracted Finger Vein

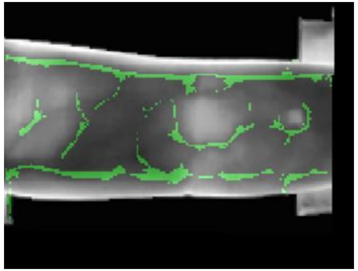


Fig. 3.2: Overlaid Finger Vein

PROPOSED METHOD (CONT.)

- **Step 3: Classification**
  - **Logistic Regression**
    - Logistic Regression is a 'Statistical Learning' technique categorized in 'Supervised' Machine Learning (ML) methods dedicated to 'Classification' tasks.
    - Logistic Regression measures the relationship between the dependent variable (our label, what we want to predict) and the one or more independent variables (our features), by estimating probabilities using it's underlying logistic function.

PROPOSED METHOD (CONT.)

- The Sigmoid-Function S(z) / logistic function is an S-shaped curve that can take any real-valued number and map it into a value between the range of 0 and 1, but never exactly at those limits. This values between 0 and 1 will then be transformed into either 0 or 1 using a threshold classifier.

$$\boldsymbol{S(z) = \frac{1}{1+e^{-z}}}$$

Here, ***S(z)*** = the output estimated probability between 0 and 1

z = the input to the function and the attempted estimated prediction

- Logistic Regression works well on large samples.

PROPOSED METHOD (CONT.)

- Logistic Regression works well on linearly separable data.

- Logistic Regression can easily extend to multiple classes (multinomial regression) and a natural probabilistic view of class predictions.

RESULT AND DISCUSSION

DATASET

- **SDUMLA-HMT [12] dataset**
    - **No of images:** 3816
    - **No. of subject:** 106
    - **Image Resolution:** 320x240 pixel

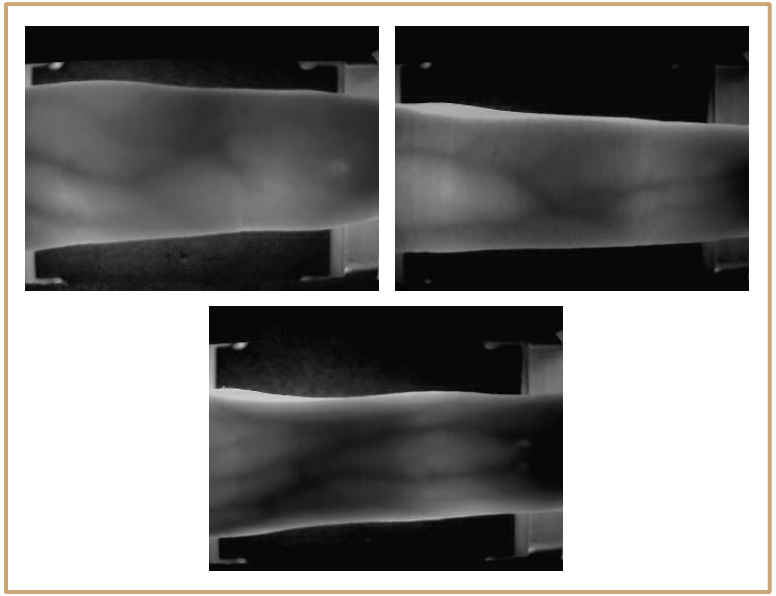


Fig. 4: Images from SDUMLA-HMT [12] Dataset

EXPERIMENTAL SETUP

The conducted tests and the algorithm of the proposed method were implemented using Python (version 3.7.5) on a PC with Intel(R) Core(TM) i5-8400 CPU, 2.80GHZ 2.81GHZ processor, 16GB RAM.

RESULT AND EVALUATION

- The classification models KNN, SVM, Random Forest, Stochastic Gradient Descent (SGD) are performed on three different train test splits in order to obtain the optimum split ratio.

RESULT AND EVALUATION (SPLIT RATIO)

Result: 75:25 ratio gives the optimal result

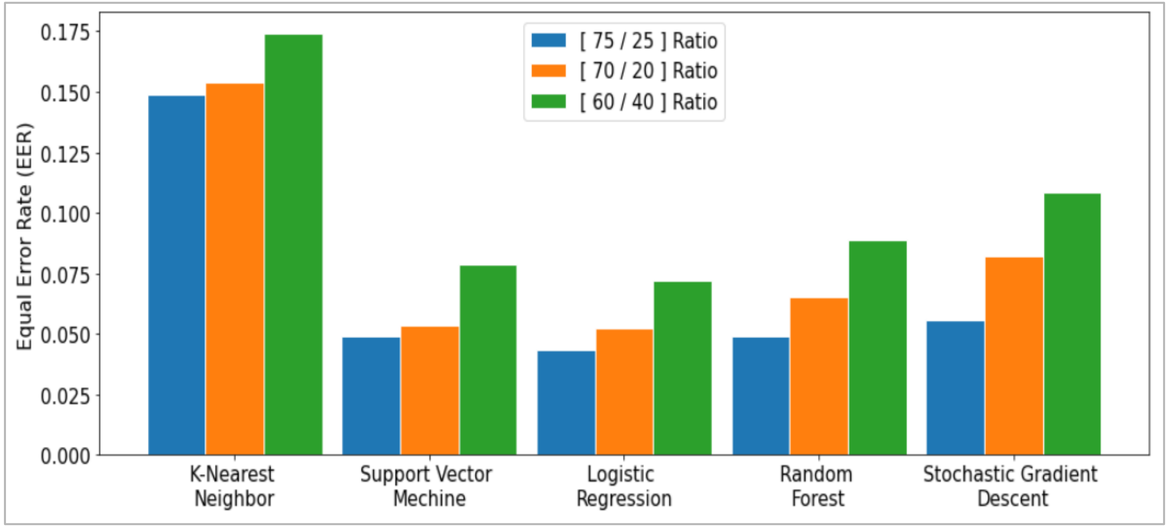


Fig. 5: An EER comparison of the existing classification model based on different split ratios

RESULT AND EVALUATION (CONT.)

- Classification models such as KNN, SVM, LR, Random Forest, Decision Tree, SGD are performed on the extracted image obtained by using the proposed method, where the dataset has been split into 75:25 ratio.

RESULT AND EVALUATION (CONT.)

Result: LR is showing better result in terms of EER.

Table. 1: Comparison of classification performance

Classifier	Accuracy	Precision	Recall Score	F1 Score	EER
KNN (n=5)	0.5409	0.6486	0.5470	0.5365	0.1490
SVM	**0.8468**	0.8549	**0.8650**	**0.8480**	0.0489
Logistic Regression	0.8438	**0.8579**	0.8614	0.8455	**0.0436**
Random Forest	0.8459	0.8525	0.8639	0.8448	0.0489
Decision Tree	0.3396	0.5271	0.3508	0.3878	0.1734
Stochastic Gradient Descent (SGD)	0.7862	0.8328	0.7973	0.7907	0.0557

RESULT AND EVALUATION (CONT.)

- Comparison of results of finger vein feature extraction and classification on SDUMLA-HMT dataset is performed.

RESULT AND EVALUATION (CONT.)

Result: Proposed MMCM shows noticeable improvement in decreasing EER in comparison to the given recent works.

Table. 2: Result performance comparison of existing finger vein extraction and classification methods

Paper	**year**	**Feature Extraction**	**Classification**	**EER**
Kumar et al. [3]	2015	Local Binary Pattern (LBP)	Multi-Support Vector Machine (SVM)	0.523
Zhou et al. [18]	2016	Superpixel over segmentation	Super-Pixel Context Feature (SPCF)	0.0697
Syarif et al. [19]	2017	Enhanced Maximum Curvature	SVM	0.14
Fang et al. [20]	2018	Mini-ROI Extraction	Two channel network learning	0.47
Proposed Method	___	**Modified Maximum Curvature**	**Logistic Regression**	**0.0436**

CONCLUSION

Conclusion

- The proposed hybrid architecture MMCM is a combination of
  - **Image Preprocessing:**
    - Region Of Interest Extraction
    - Enhancement with CLAHE
    - Noise Reduction with Gaussian Filter
    - Affine Transform Normalization
  - **Feature Extraction:**
    - MCM
  - **Classifier:**
    - LR

Conclusion (CONT.)

- MMCM outperforms existing finger vein authentication methods with a reasonable EER of 0.043.
- The LR model performs well on multi class classification.

FUTURE WORK

FUTURE WORK

- Implementation of a Deep Learning model for classification
- Performing the proposed model on comprehensive datasets

REFERENCE

REFERENCE

[1] Naoto Miura, Akio Nagasaka, and Takafumi Miyatake. Extraction of finger-vein patterns using maximum curvature points in image profiles. *IEICE TRANSACTIONS on Information and Systems*, 90(8):1185–1194, 2007.

[2] Shan Juan Xie, Sook Yoon, Jucheng Yang, Yu Lu, Dong Sun Park, and Bin Zhou. Feature component-based extreme learning machines for finger vein recognition. *Cognitive Computation*, 6(3):446–461, 2014.

[3] R Prem Kumar, Rachit Agrawal, Surbhi Sharma, Malay Kishore Dutta, Carlos M Travieso, Jesus B Alonso-Hern´ andez, et al.´ Finger vein recognition using integrated responses of texture features. In *2015 4th International Work Conference on Bioinspired Intelligence (IWOBI)*, pages 209–214. IEEE, 2015.

[4] Chenguang Liu and Yeong-Hwa Kim. An efficient finger-vein extraction algorithm based on random forest regression with efficient local binary patterns. In *2016 IEEE International Conference on Image Processing (ICIP)*, pages 3141–3145. IEEE, 2016.

[5] Shereen S Jumaa and Khamis Zidan. Finger vein recognition using two parallel enhancement ppproachs based fuzzy histogram equalization. *Periodicals of Engineering and Natural Sciences*, 7(1):514–529, 2019.

[6] Ruqaiya Khanam, Ramsha Khan, and Rajeev Ranjan. Analysis of finger vein feature extraction and recognition using da and knn methods. In *2019 Amity International Conference on Artificial Intelligence (AICAI)*, pages 477–483. IEEE, 2019.

REFERENCE (CONT.)

[7] Insha Qayoom and Sameena Naaz. Discriminant analysis and na¨ıve bayes classifier-based biometric identification using finger veins. *International Journal of Computer Vision and Image Processing (IJCVIP)*, 9(4):15–27, 2019.

[8] Xianjing Meng, Xiaoming Xi, Zongwei Li, and Qing Zhang. Finger vein recognition based on fusion of deformation information. *IEEE Access*, 8:50519–50530, 2020.

[9] Ajay Kumar and Yingbo Zhou. Human identification using finger images. *IEEE Transactions on image processing*, 21(4):2228–2244, 2011.

[10] Jian-Da Wu and Chiung-Tsiung Liu. Finger-vein pattern identification using principal component analysis and the neural network technique. *Expert Systems with Applications*, 38(5):5423–5427, 2011.

[11] Jian-Da Wu and Chiung-Tsiung Liu. Finger-vein pattern identification using svm and neural network technique. *Expert Systems with Applications*, 38(11):14284–14289, 2011.

[12] Yilong Yin, Lili Liu, and Xiwei Sun. Sdumla-hmt: a multimodal biometric database. In *Chinese Conference on Biometric Recognition*, pages 260–268. Springer, 2011.

[13] Mohd Shahrimie Mohd Asaari, Shahrel A Suandi, and Bakhtiar Affendi Rosdi. Fusion of band limited phase only correlation and width centroid contour distance for finger based biometrics. *Expert Systems with Applications*, 41(7):3367–3382, 2014.

REFERENCE (CONT.)

[14] Bram T Ton and Raymond NJ Veldhuis. A high quality finger vascular pattern dataset collected using a custom designed capturing device. In *2013 International conference on biometrics (ICB)*, pages 1–5. IEEE, 2013.

[15] Jong Min Song, Wan Kim, and Kang Ryoung Park. Finger-vein recognition based on deep densenet using composite image. *IEEE Access*, 7:66845–66863, 2019.

[16] Eui Chul Lee, Hyeon Chang Lee, and Kang Ryoung Park. Finger vein recognition using minutia-based alignment and local binary pattern based feature extraction. *International Journal of Imaging Systems and Technology*, 19(3):179–186, 2009.

[17] Beining Huang, Yanggang Dai, Rongfeng Li, Darun Tang, and Wenxin Li. Finger-vein authentication based on wide line detector and pattern normalization. In *2010 20th international conference on pattern recognition*, pages 1269–1272. IEEE, 2010.

[18] Lizhen Zhou, Gongping Yang, Yilong Yin, Lu Yang, and Kuikui Wang. Finger vein recognition based on stable and discriminative superpixels. *International Journal of Pattern Recognition and Artificial Intelligence*, 30(06):1650015, 2016.

[19] Munalih Ahmad Syarif, Thian Song Ong, Andrew BJ Teoh, and Connie Tee. Enhanced maximum curvature descriptors for finger vein verification. *Multimedia Tools and Applications*, 76(5):6859–6887, 2017.

[20] Yuxun Fang, Qiuxia Wu, and Wenxiong Kang. A novel finger vein verification system based on two-stream convolutional network learning. *Neurocomputing*, 290:100–107, 2018.

THANK YOU