A HYBRID SEGMENTATION SCHEME FOR IMPROVED DORSAL HAND VEIN RECOGNITION

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I owe immense sense of gratitude and dedicate this work to my beloved parents and supervisor who not only supported me financially but also gave me confidence throughout the career.

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ABSTRACT

The dorsal hand vein (DHV) pattern is a highly secured biometric system that is significantly used in many applications due to its uniqueness. Although it is a safe and secure means for biometric identification, accurate recognition of vein patterns for this application remains challenging. To solve the issue, various machine learning (ML) and deep learning (DL) techniques were employed in the past to identify DHV correctly. A hybrid ML and DL strategy are adopted in this study. An automatic segmentation technique designed based on the histogram, thresholding and morphological operations is proposed to overcome the shortcomings of manual segmentation. The Bosphorus database is used for demonstration. While the first set of the experiment used the original segmented dataset, the second combines the original dataset with the augmented images generated using the combinations of rotation transformations (i.e., [30˚ -30˚] and [50˚ -50˚]) and flipping. The results comparing the performance of AlexNet, which is used as the baseline, revealed a considerable difference between the outputs trained using manual and automatically segmented datasets with a classification accuracy of 87.5% and 76.5 %. This difference in accuracy is significantly reduced to 4 % with the augmentation methods i.e., 91.5 % and 88 %. Interestingly, the inclusion of augmentation does not increase the performance in the manual likely because the existing data is sufficient for the model to learn all core features. The proposed segmented set with augmentation is further supported by the good classification performance of GoogleNet and ResNet-18. The mean and standard deviation of AlexNet, GoogleNet and ResNet-18 in their classification accuracy, sensitivity, and specificity are given by 99.79±0.098 %, 89.5±4.92 %, and 99.89±0.05 %. The ResNet-18 achieved superior performance with less training time than GoogleNet on the DHV dataset, which can be attributed to its capacity to address the network degradation issue. This work recommends the proposed framework and a deep model with skip connections, such as ResNet-18 for use in recognizing DHV patterns for future authentication research and system development.

ABSTRAK

Sistem pengecaman corak urat pada permukaan dorsal tangan adalah satu sistem biometrik yang paling selamat kerana sifatnya yang sangat unik bagi setiap orang. Namun masih terdapat kekurangan dan cabaran dalam kaedah pengesahan yang berasaskan urat tangan dorsal. Untuk mengatasi isu ini, pelbagai kaedah pembelajaran mesin dan model pembelajaran mendalam telah digunakan dalam pengkelasan corak urat tangan. Dalam kajian ini, pendekatan pembelajaran mesin hibrid dan pembelajaran mendalam dicipta untuk tujuan ini. Teknik segmentasi secara automatik yang berdasarkan taburan histogram, penentuan nilai ambang, dan operasi morfologi telah dicadangkan untuk mengatasi kelemahan kaedah segmentasi secara manual. Imej urat tangan dorsal tangan yang diperoleh daripada pangkalan data Bosphorus telahpun digunakan. Experimen pertama melibatkan menggunakan data asal, manakala kedua menggabungkan data asal dan data baru yang dijana melalui transformasi posisi (sudut [30˚ -30˚] dan [50˚ -50˚]) dan direksi. Perbandingan keputusan AlexNet menggunakan data yang diperolehi dari process segmentasi secara manual dan automatik menunjukkan perbezaan yang ketara dengan skor 87.5% dan 76.5%. Perbezaan ini telah dikurangkan kepada 4% melalui penggunaan data tambahan. Yang menariknya, penambahan data tambahan tidak meningkatkan prestasi dalam kaedah manual. Ini mungkin kerana data sediaada adalah mencukupi untuk model mempelajari semua ciri penting dalam data. Kecekapan pendekatan ini disokong dengan keputusan baik yang diperolehi melalui GoogleNet dan ResNet-18. Purata ketepatan pengelasan, kepekaan dan kekhususan adalah dengan skor 99.79±0.098 %, 89.5±4.92 %, and 99.89±0.05 %. ResNet-18 telah mencapai hasil prestasi yang baik. Kerja ini mengesyorkan supaya pendekatan yang dicadangkan berserta model pembelajaran mendalam seperti ResNet-18 digunakan dalam pembangunan sistem pengecaman corak urat tangan pada masa hadapan.

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LIST OF SYMBOLS AND ABBREVIATIONS

2D	–	Two dimensional
3D	–	Three dimensional
AHE	–	Adaptive Histogram Equalization
AI	–	Artificial Intelligence
ANN	–	Artificial Neural Network
Aug-HHM	–	Hybrid automatic segmentation with augmentation
aug-manual	–	Manually cropped with augmentation
Bmp	–	Bitmap
CCD	–	Charge coupled device
CLAHE	–	Contrast-limited Adaptive Histogram Equalization
CMOS	–	Complimentary monochrome metal oxide semiconductor
CNN	–	Convolution Neural Network
Conv	–	Convolution layer
CPU	–	Central Processing Unit
DHV	–	Dorsal hand vein
DL	–	Deep learning
DNA	–	Deoxyribonucleic acid
DNN	–	Deep Neural Network
DRF	–	Deep Residual Features

Drop	–	Dropout layer
DSLR	–	Single-lens reflex camera
ECOC	–	Error Correcting Output Codes
FC	–	Fully Connected layer
FN	–	False negative
FP	–	False positive
GAN	–	Generative adversarial network
GPU	–	Graphics Processing Unit
HE	–	Histogram Equalization
HHM	–	Hybrid automatic segmentation
IITD	–	Indian Institute of Technology Delhi
IM	–	Inception Modules
IR	–	Infrared
kNN	–	k-nearest neighbor
LBP	–	Local Binary Pattern
LED	–	Light emitting diode
LOG	–	Laplacian of Gaussian
LRN	–	Local Response Normalization
LSTMs	–	Long Short-Term Memory Networks
M	–	Million
MATLAB	–	Matrix Laboratory
ML	–	Machine learning
n	–	Epoch
η	–	Initial learning rate
NCUT	–	North China University of Technology
NIR	–	Near-infrared
Ø	–	Moment invariants

O/P	–	Output
PLBP	–	Partition Local Binary Pattern
Prob	–	Softmax layer
ReLU	–	Rectified Linear Unit
RF	–	Random Forest
RGB	–	Red Green Blue
RNN	–	Recurrent Neural Network
ROI	–	Region of interest
SE	–	Structuring element
SGDM	–	Stochastic gradient descent with momentum
SVM	–	Support Vector Machine
SVs	–	Support Vectors
SNR	–	Signal to noise ratio
TN	–	True negative
TP	–	True positive
VGG	–	Visual Geometry Group
VPR	–	Vein pattern recognition
β	–	Mini-batch size
dm	–	Mahalanobis distance

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Overview

This chapter provides the background information of this research. The background of the dorsal hand vein recognition system is discussed in section 1.2. In section 1.3, the problems concerning the existing systems are briefly explained. The aims and scopes of this research are presented in sections 1.4 and 1.5, followed by research contributions in section 1.6. The organization of the remaining chapters is presented in section 1.7.

1.2 Background of study

Nowadays, an automatic personal recognition system based on biometric methods plays an important role in many applications, such as in high-security offices, public banks and education sectors [1]. The application and implementation of a biometric system demands the following requirements: universality, distinctiveness, permanence, and collectability. A biometric system can be classified into two types: human physiological and behavioural characteristics identification system [2, 3]. The physical biometric systems are such as fingerprints [4], palm print, dorsal hand vein [5], and face identification [6], and iris of the eye recognition [7], while the behavioural characteristics include that of the keystrokes [8], gait, and voice [9].

Poor and inefficient security capabilities are the main concern in many biometric systems. The vulnerable and weak security mechanisms cause fraud, privacy loss, money laundering, and other confidentiality problems. Thus, different biometric techniques have been designed to overcome the problem.

The fingerprint is the most common personal identification system in our society, but it can be easily fooled by capturing the prints and printing on gelatin material board, and there are even cases where fingerprints are not recognized due to scratches in the fingers because of injury and skin diseases. Similarly, a face recognition system is also currently being used in growing numbers of applications. Even though this technique is able to recognize the person from a distance, the major problems associated with the system are processing speed and storage, surveillance angle, light variations, and inter-class variability [6].

The iris of different individuals varies, so it can be used for personal identification. However, iris is sensitive to light and it cannot be scanned with glasses on. Thus, many researchers diverted their focus towards the dorsal hand vein biometric system because, unlike the iris, its pattern can be easily seen with naked eyes and the technique is comparatively more robust to the environmental changes. The dorsal hand vein was first proposed to be used in biometric technology in 1992 [10]. Example of hand vein patterns is as shown in Figure 1.1.

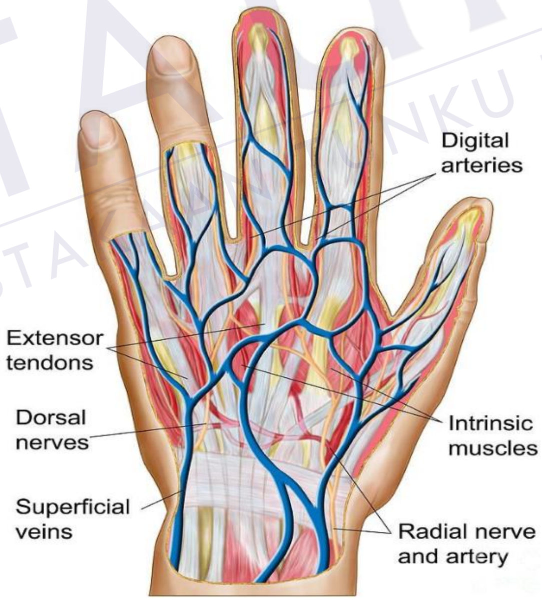

Figure 1.1: Pattern of dorsal hand vein [1].

The pattern of a vein is formed by a capillaries network of blood vessels that carry deoxygenated blood from the body to the heart beneath the person’s skin. Thus, it cannot be copied or fooled easily. This type of biometric system is contactless, hygienic and is not affected by external condition of the skin, such as dirt or skin disease. It has a unique biometric feature similar to that of fingerprints and iris.

Everyone possesses a different pattern of veins, even among twins. Thus, it is difficult to be forged. Besides, dorsal hand vein does not change with time. Consequently, it is stable enough regardless of the ageing effect and environmental conditions, such as temperature and humidity [1].

The main factor affecting the overall quality and clarity of hand veins image is the imaging system used. There are many devices that have been proposed to capture the dorsal hand vein images, such as near-infrared (NIR) camera [11, 12], complimentary monochrome metal oxide semiconductor (CMOS) [13] and digital single-lens reflex camera (DSLR) [14]. To avoid the unnecessary information of dorsal hand vein images, segmentation techniques can be used. By doing that, the background of dorsal hand vein images can be eliminated and the veins' pattern can be further enhanced, which may improve the recognition accuracy. Various segmentation approaches have been introduced in the past with varying degrees of success. The image delineation can either be carried out manually [15] or automatically [16] to the extract Region of Interest (ROI) of dorsal hand vein images.

To extract the features of dorsal hand vein pattern, machine learning and deep learning (DL) methods were adopted in the past. DL automatically performs feature extraction and modeling after data training, whereas machine learning requires data scientists or users to extract and create features. Classic network architecture of DL includes Long Short-Term Memory Networks (LSTMs), Recurrent Neural Network (RNN), Convolution Neural Network (CNN) and Deep Neural Network (DNN). The classification accuracy depends on the network architecture and training methods, the input features, and the size of dataset. Among which, CNN has been extended to resolve multiple computer vision and pattern recognition challenges with great success by employing deeper architectures [17], improved training technologies such as Dropout [18], and better nonlinear activation functions such as Rectified Linear Unit (ReLU). Moreover, this technique requires minimal image pre-processing steps due to its ability to combine segmentation, feature extraction, and classification in one module. There are several pre-trained CNN models available for use, such as AlexNet [19], ResNet [20], GoogleNet [21], SqueezeNet [22] and Visual Geometry Group (VGG) [23]. Each differed in their feature extraction scheme and data transformation.

As the convolution layers become increasingly deep, their training errors and testing errors could become low, but this is at the price of higher computation time [20]. GoogleNet comprises of 22 layers, which is deeper than other models.

Meanwhile AlexNet has comparatively shallow architecture. AlexNet was also reported to achieve comparable training performance to the deeper counterpart (VGG16 and VGG19) with lesser computational resources. In addition, the performance of the model also depends upon the size of dataset. The higher the number of images in a dataset, the better the model can recognize the important features in the dataset, thus the higher the model inference accuracy. Augmentation scheme is another strategy often introduced to enlarge the dataset for avoiding model overfitting during the training.

1.3 Problem statement

Behavioral characteristics are unsecure and less reliable means of biometric system e.g., keystroke such as password can be easily hacked or copied. However, traditional physical characteristics include several significant flaws, such as angular problem in the case of facial recognition system [6] and iris is sensitive to light radiation. To overcome these problems, researchers focused on dorsal hand vein. This biometric system is secured and unaffected by environmental variations such as temperature because it is found inside the skin.

In order to properly recognize an image, ROI must be accurately known, segmented and analyzed separately. However, the present gold standard method using manual segmentation approach demonstrated in [15, 24] has several key shortcomings, including the high degree of variability in the outcomes because the process is dependent on intuition rather than objective analysis. In other words, the segmented results differ for each image due to the manual nature of the process. In addition, a small portion of vein may be vanished during segmentation. Therefore, researchers diverted their focus towards automatic segmentation. The authors in [25] used hybrid segmentation by combining morphological and local thresholding to extract the pattern of dorsal hand vein, but this algorithm requires a compensation method for the breakpoints (i.e., background and fingers) of dorsal hand vein in getting rid of the noise. In most cases, the robustness of the proposed segmentation methods was tested on small datasets [16]. This calls for further research, and a more generalized and rigorous evaluation on the automatic segmentation methods that are both effective and time efficient.

Meanwhile DL is especially useful in domains with large and multidimensional datasets. Some have developed their own CNN model, but this requires training on a large collection of data. A pre-trained model that has been extensively trained on very large-scale dataset can be employed for classifying new/unseen classes by fine-tuning its neurons' weights. This technique was adopted in [26] using AlexNet in their demonstration, but the work lacks evaluation on the trained model because no unseen data were used to test model predictions. In addition, the authors in [26] used whole images, wherein the model is likely trained to identify hand contour and position instead of vein patterns. Meanwhile authors in [27] used augmentations strategy with several well-known models, i.e., AlexNet, ResNet-50 and ResNet-152 to enhance the testing accuracy, but the authors reported expensive computational power (i.e., required high processing speed) in case of ResNet-152. There remains a need of identifying the best model in terms of computational time and performance for classification of dorsal hand vein datasets. An efficient segmentation and classification framework for dorsal hand vein pattern recognition is highly necessary for secure biometric system.

1.4 Objectives

This research study focuses on the following objectives:

a) To propose a hybrid automatic segmentation approach for dorsal hand vein recognition.
b) To investigate and compare the performance of the developed automatic and gold standard segmentation technique.
c) To compare the performance of different 2D CNN models and to recommend the best model for identity authentication.

1.5 Scopes of study

The scope of the research is:

a) A hybrid technique is developed by combining histogram equalization, morphological operation and thresholding algorithm for vein region delineation.

b) To compare the performance of the baseline AlexNet trained using automatic segmentation with manual cropped (gold standard) datasets.
c) To recommend the best model for dorsal hand vein pattern recognition from the comparison of the inference accuracy, specificity and sensitivity of AlexNet, ResNet-18 and GoogleNet.

1.7 Research contributions

In this study, an automatic segmentation and classification scheme for dorsal hand images is proposed. The main contributions of this research are summarized as followed:

a) An automatic method has been proposed to extract the ROI of dorsal hand vein images. This method is comparatively more effective and time efficient than the manual technique with 10 folds shorter processing time.
b) The proposed framework combining the automatic segmentation and classification system produces a relatively good and rapid recognition result with a mean classification accuracy of 89.5 %, which is crucial for a robust biometric system.

1.8 Thesis layout

The structure of the remaining thesis is as followed:

Chapter 2 includes the past works related to this thesis, and discussion of basic terminology, applications, and research regarding this topic.

Chapter 3 describes the design, component and working principle of the proposed system in achieving the expected outcomes.

Chapter 4 presents the results and discussions of this study. This chapter also compares the performance of various CNN models used in this research.

Chapter 5 demonstrates the research conclusion and recommendations. This chapter also highlights the future works that need to be addressed and resolved to maximize the performance of the system.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

This chapter includes the past reviews related to the techniques and methods using hand vein pattern as the authentication of identities. This chapter begins with the introduction of different types of biometric systems, their characteristics and performance, and previous studies that utilized these methods in section 2.2.

The imaging system available for the dorsal hand vein authentication research and the public available databases are elaborated in section 2.3 and 2.4. The segmentation methods used for making decisions on image delineation are discussed in section 2.5. The commonly used approaches for image classification, and their method in section 2.6, together with the available optimization techniques and augmentation strategy are presented in sections 2.7 and 2.8. The past works related to dorsal hand veins authentication are summarized in section 2.9.

2.2 Overview of biometric system

The word “biometric” is the combination of two Greek words, “bios” (life) and “metrikos” (measure) [28]. Therefore, it is referred to the analysis of human characteristics, either physical or behavioural [2, 3]. The physical characteristics include fingerprint, palm print, face, iris, dorsal hand vein, and palm vein while the behavioural consists of the keystroke, signature as shown in Figure 2.1. Biometric system is mainly introduced for security and assurance purposes for use in e.g., banks [1]. Everyone possesses unique characteristics, such as iris of an eye, fingerprints, and dorsal hand vein so it is not easily transferable.

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APPENDIX A

LIST OF PUBLICATIONS

1. **W. A. Laghari**, K. G. Tay, A. Huong, Y. Y. Choy, and C. C. Chew, "Dorsal Hand Vein Identification using Transfer Learning from AlexNet," International Journal of Integrated Engineering (IJIE), vol. 14, no. 3, pp. 111–119, 2022.
2. F. K. Baloch, G. E. M. Abro, **W. A. Laghari**, Z. A. Soomro, A. A. Rahimoon, and R. Kumar, "Controlling and Monitoring of Hybrid Power System Using an Android Application.," IEEE 5th International Symposium in Robotics and Manufacturing Automation, August 6-8, pp. 1–5, 2022.
3. **W. A. Laghari**, K. G. Tay, C. C. Chew, and A. Huong. Dorsal Hand Vein Pattern Recognition: Comparison between manual and automatic segmentation methods. (*Manuscript submitted to Healthcare Informatics Research).*

APPENDIX B

VITA

Waheed Ali Laghari was born on May 5, 1998, in Dadu, Pakistan. He went to British Model high school Dadu, Sindh, Pakistan for his secondary education. He pursued his degree at the Mehran University of Engineering and Technology, Jamshoro, Pakistan, and graduated with the Bachelor of Engineering (BE) in Electrical Engineering in 2019. Currently, he is pursuing Master degree in Electronic Engineering at University Tun Hussein Onn Malaysia, Malaysia. His research interests include deep learning and image processing, with application to authentication.