MODEL-BASED 3D GAIT BIOMETRIC USING QUADRUPLE FUSION CLASSIFIER

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A thesis submitted in fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy (Computer Science)

Faculty of Computing
Universiti Teknologi Malaysia

SEPTEMBER 2017

DEDICATION

To my husband Mohd Sujairi and
children Asma', Abdullah Mouaz and Abdullah Mouiz

ACKNOWLEDGEMENT

In the name of Allah, the Most Gracious and the Most Merciful. Praise be to Allah, Lord of the Universe and to His Messenger, Muhammad PBUH. I praise and thank to Allah, the Almighty for giving me the strength, courage, and blessings to complete this thesis.

First and foremost I offer my sincerest gratitude to my supervisor, Prof. Dr. Azizah Abdul Manaf who has supported me throughout my PhD journey with her patience and expertise. She has made available her support in a number of ways, especially towards the completion of this thesis. I also would like to thank Dr Shahrizal Sunar for his assistance during data collection process in UTM Skudai.

I would like to thank Ministry of Higher Education for funding my studies for this PhD programme. In my daily work I have been blessed with a friendly and cheerful group of friends. My special gratitude goes to my friends Shahida, Suhada, Sidah, Rohani, Salwani and Ummihani for their encouragement at all times. My special thanks also go to Dr. Hazlifah, all the staff at AIS and co- researchers at UTM who have helped me in many ways to complete this research.

I am also thankful to my family for their continuous and unparalleled love, help and support. I am grateful to my brothers and sister for always being there for me. At last and most importantly, this programme would not have been possible without the support of my husband, Mr. Mohd Sujairi Othman. I am thankful for his endless patience and love, consistent support and motivation for me to be where I am at present.

ABSTRACT

The area of gait biometrics has received significant interest in the last few years, largely due to the unique suitability and reliability of gait pattern as a human recognition technique. The advantage of gait over other biometrics is that it can perform non-intrusive data acquisition and can be captured from a distance. Current gait analysis approach can be divided into model-free and model-based approach. The gait data extracted for identification process may be influenced by ambient noise conditions, occlusion, changes in backgrounds and illumination when model-free 2D silhouette data is considered. In addition, the performance in gait biometric recognition is often affected by covariate factors such as walking condition and footwear. These are often related to low performance of personal verification and identification. While body biometrics constituted of both static and dynamics features of gait motion, they can complement one another when used jointly to maximise recognition performance. Therefore, this research proposes a model-based technique that can overcome the above limitations. The proposed technique covers the process of extracting a set of 3D static and dynamic gait features from the 3D skeleton data in different covariate factors such as different footwear and walking condition. A skeleton model from forty subjects was acquired using Kinect which was able to provide human skeleton and 3D joints and the features were extracted and categorized into static and dynamic data. Normalization process was performed to scale down the features into a specific range of structure, followed by feature selection process to select the most significant features to be used in classification. The features were classified separately using five classification algorithms for static and dynamic features. A new fusion framework is proposed based on score level fusion called Quadruple Fusion Framework (QFF) in order to combine the static and dynamic features obtained from the classification model. The experimental result of static and dynamic fusion achieved the accuracy of 99.5% for footwear covariates and 97% for walking condition covariates. The result of the experimental validation demonstrated the viability of gait as biometrics in human recognition.

ABSTRAK

Bidang biometrik gaya berjalan telah mendapat perhatian yang ketara sejak beberapa tahun lepas, sebahagian besarnya disebabkan oleh kesesuaian yang unik dan kebolehpercayaan corak gaya berjalan sebagai teknik pengenalan manusia. Kelebihan gaya berjalan berbanding biometrik lain adalah ia boleh melakukan rakaman data tanpa diganggu dan boleh dirakam dari jauh. Pendekatan analisis gaya berjalan masa kini boleh dibahagikan kepada pendekatan model bebas dan berdasarkan model. Data gaya berjalan diekstrak untuk proses pengenalan boleh dipengaruhi oleh keadaan bunyi, sekatan gambar, perubahan di latar belakang dan pencahayaan apabila bayang model bebas data *2D* digunakan. Di samping itu, prestasi dalam pengiktirafan biometrik gaya berjalan sering dipengaruhi oleh faktor-faktor kovariat seperti keadaan berjalan kaki dan kasut. Ini sering dikaitkan dengan prestasi rendah untuk pengesahan peribadi dan pengenalan. Biometrik badan termasuk kedua-dua pergerakan gaya berjalan berciri statik dan dinamik, dan kedua-duanya boleh saling melengkapi antara satu sama lain apabila digunakan bersama-sama untuk memaksimumkan prestasi pengiktirafan. Oleh itu, kajian ini mencadangkan teknik berdasarkan model yang boleh mengatasi kelemahan yang disebutkan di atas. Teknik yang dicadangkan meliputi proses mengekstrak satu set *3D* ciri gaya berjalan statik dan dinamik daripada data rangka 3D dalam faktor-faktor kovariat yang berbeza seperti kasut yang berbeza dan keadaan berjalan kaki. Satu model rangka dari empat puluh orang peserta telah diambil dengan menggunakan *Kinect* yang mana ia boleh memberikan rangka manusia dan rangka 3D dan ciri-ciri ini telah dirakam dan dikategorikan kepada data statik dan dinamik. Proses normalisasi telah dilakukan untuk menuruni ciri-ciri ke dalam julat tertentu struktur, diikuti oleh proses pemilihan ciri untuk memilih ciri-ciri yang paling penting untuk digunakan dalam pengelasan. Ciri-ciri ini telah dikelaskan secara berasingan dengan menggunakan lima algoritma pengelasan untuk ciri-ciri statik dan dinamik. Rangka kerja fusion baru adalah dicadangkan berdasarkan gabungan tahap skor dipanggil Kerangka Pelakuran Empat-Lipat (QFF) untuk menggabungkan ciri-ciri statik dan dinamik yang diambil dari model klasifikasi. Hasil eksperimen pelakuran statik dan dinamik mencapai ketepatan 99.5% untuk kovariat kasut dan 97% untuk kovariat keadaan berjalan. Hasil pengesahan eksperimen menunjukkan gaya berjalan boleh diiktiraf sebagai biometrik yang berdaya maju.

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LIST OF ABBREVIATIONS

2D	-	Two-Dimensional
3D	-	Three-Dimensional
AUC	-	Area Under Curve
BN	-	Bayesian Network
BVH	-	Biovision Hierarchy
CASIA	-	Chinese Academy of Sciences Institute of Automation
CGI	-	Chrono-Gait Image
CMS	-	Cumulative Match Score
CSV	-	Comma-Separated Values
GEI	-	Gait Energy Image
GEnI	-	Gait Entropy Image
GFI	-	Gait Flow Image
GHz	-	Gigahertz
GRF	-	Ground Reaction Forces
GUI	-	Graphical User Interface
K-NN	-	K-Nearest Neighbour
LED	-	Light-Emitting Diodes
MATLAB	-	Matrix Laboratory
EER	-	Equal Error Rate
FA	-	False Accept
FN	-	False Negative
FP	-	False Positive
FR	-	False Reject
FAR	-	False Acceptance Rate
FDF	-	Frequency-Domain Feature
FPS	-	Frames Per Second
FRR	-	False Rejection Rate

MBL	-	Memory-Based Learning
MDA	-	Multiple Discriminant Analysis
MLP	-	Multilayer Perceptron
PC	-	Personal Computer
PCA	-	Principal Component Analysis
PIN	-	Personal Identification Number
RAM	-	Random Access Memory
RGB	-	Red-Green-Blue
ROC	-	Receiver Operating Characteristic
RPM	-	Rotations Per Minute
SDK	-	Software Development Kit
STHOG	-	Spatio-Temporal Histogram of Oriented Gradient
SVD	-	Singular Value Decomposition
SVM	-	Support Vector Machine
TP	-	True Positive
TN	-	True Negative
TRC	-	Track Row Column
USB	-	Universal Serial Bus
UTM	-	Universiti Teknologi Malaysia
WEKA	-	Waikato Environment for Knowledge Analysis
XLS	-	Excel Spreadsheet

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CHAPTER 1

INTRODUCTION

This chapter begins with a brief introduction on the subject of the research, i.e. fusion of static and dynamic features for gait biometric recognition. Firstly, the background of the problem is described and statement of the problem is defined. This is then followed by the objectives and scope of this research. The final section contains the significance of this research and the synopsis of this research in thesis outline.

1.1 Background of the Problem

In recent years, there has been an increase in authentication action in humans' daily lives. Common activities such as cash withdrawal from auto teller machines, login into personal computers, unlocking the mobile phones or immigration checks while entering a country requires authentication through PIN numbers, passwords or identification documents. Despite the simplicity and ease of use, these practises have a number of problems and errors. The disadvantages of these practices are that they can be stolen, lost, misplaced or forgotten [1]. The lost magnetic cards can be used by the unlawful users. The weakness of passwords or PIN codes can be guessed easily, hence, giving access to resources such as bank accounts, medical records or personal tax records. In terms of immigration checks, many intruders have successfully entered a country using fake documents. Based on these complications of weak credentials, another authentication method that cannot be stolen, misplaced, easily forged or forgotten is needed in order to provide resilient security, efficient, faster and automated approach.

Issues of traditional authentication methods and recent developments in the field of security have led to a renewed interest in biometric technology [2]. Biometrics uses human's biological and behavioural characteristics as a personal authentication measurement, hence overcoming the problem of lost or forgotten ID. Currently, face, iris and fingerprint biometrics are the most popular and reliable choice for authentication for certain systems and applications. In some scenarios such as immigration checks at airports which involve a huge amount of people, a system with reliable security and faster processing time are the important aspect to be considered for passanger identity check [1]. Whilst fingerprint and face are chosen by immigration as biometrics technologies of authentication security, they suffer from problems such as lost of fingerprints or quality of fingerprints that is not sufficient for enrolment [3], [4]. The overall average time for passenger verification process is reduced when processing bigger data such as face biometric. Other disadvantages of commonly used biometrics include low image resolutions and the need for active user participation. Some techniques for data acquisition uses invasive technique by using sensors or markers and uncertain measurements may also cause some problems and disadvantages that influence the recognition performance and efficiency of biometrics practice [5]. Several attempts have been made to overcome this matter by either improving the current biometrics modalities or by exploring new biometrics modalities. More recently, the problem has received extra attention in research literatures and it is found that gait biometrics has the potential to satisfy many of the performance requirements.

Gait is considered as one of the behavioural types of biometrics. In general, gait biometric refers to automatic human identification based on their walking manner. Many researches have suggested that gait is unique and has been proposed as a biometric method for security applications [6-8]. The main advantage of gait over other biometric modalities is that it is capable to be recorded at distance without needing physical information from the subjects. Gait is also unobstrusive as it does not need subject's cooperation, non-invasive and easy to be set up in public areas.

Gait is difficult to disguise or obscure because the manner of walking is usually observable while other biometrics can be camorflage. Moreover, gait is indetifiable to a person even by using low resolution video or images thus making gait biometrics capable to be implemented in high throughput environment.

Generally, methods in gait biometrics can be divided into two categories namely model-free and model-based approaches. Model-free approaches acquire gait parameters by performing shape extraction from every frame of the video sequence. The measurement characteristics vector is done directly on 2D images based on the subject structure or movement without adopting specific model of human body [9-11]. Different authors have measured 2D gait data as susceptible to illumination, background noise, occlusion and shadow. The various issues in adopting 2D data caused some problems in delivering accurate and fast recognition results. Previous studies that have based their approaches on model-free approaches mostly reflects geometric-based representations like silhouette, history of movement, joint trajectories and optical flow [12-14]. The methods deliberated the measurement of individual movements together with the individual appearance without considering gait dynamics. Therefore, the methods are less sensitive to covariate factors that result in variation of gait dynamics like walking speed but more liable to factors that effect in the changes of appearances such as clothing or obesity, changes of view and direction of movement [15, 5]. One of the alternative solutions to overcome these common problems is by using model-based approaches.

The model-based approach is one of the more practical ways and has demonstrated efficient and effective ways for representing human motion and thus adopted in numerous gait recognition researches [16, 17]. Model-based approaches develop the human body model and its movements in 3D and perform acquisition on gait parameters like body dimensions, human skeleton, joint kinematics, orientations and locations of body parts, steps dimension, etc. from this model [1, 16, 18, 17]. Clearly, 3D gait dataset based on model-based approaches convey more information than 2D model-free dataset. By using 3D gait dataset, it illustrated natural representation and a more realistic human gait. Furthermore, 3D data are inherently view invariant hence it can be synthesized at any view by simple projection.

However most of the model-based approaches provide an intuitive interpretation of gait images at the cost of computational complexity out of geometrical transformations. Ariyanto [1] used a model fitting approach with a structural model in 3D space for gait tracking method and 3D model-based method based on marionette and mass-spring models. Although these methods presented certain advantage of reliability and robustness, they suffer from high computational cost and complicacy due to the large number of parameter space and also the issue of image quality and sensitivity. The complexity involved for constructing a general model describing the structural or dynamical gait components affect the fitting model for feature extraction [19]. Furthermore, the derived knowledge has none of 3D skeleton information. To overcome the difficulty and complexity in 3D model-based approach, Microsoft Kinect is introduced to reduce the computational burden. Kinect enables skeleton-detection and tracking of people in real-time by an integrated depth camera [20]. The data captured using Kinect is completely different from methods using normal cameras as it delivers tracking of different skeletal points which eliminate the computational burden of constructing model for model fitting. For that reason, it is necessary to investigate the useful benefits of using Kinect for 3D model-based approaches. It is also believed that 3D approaches might provide a more effective way of handling latent issues in 2D such as occlusion, noise, scale and varying view.

Although various gait recognition techniques established significant performance under controlled environment setups, the covariate factors that influence individual's gait make the gait recognition task in real-life non-realistic and limited. There are a number of covariate factors that can change gait characteristics such as clothing, footwear, speed, direction and changes of view that can be considered as external factors and changes due to injuries, illness, pregnancy or aging as internal factors [21]. Recent studies have considered the covariate factors of speed and injuries in real life applications to detect anomalies in residents' movements in monitoring gait motion characteristics of residents in senior housing [22]. Based on these circumstances, covariate factors must be considered in order to make the gait data meaningful for gait analysis.

Current research on gait analysis suggests that gait recognition can be derived from either static or dynamic features. Several model based approaches have focused on gait dynamics and fewer on appearance of individual which represent static data The results achieved were more resistant to problems like changes of view and scale but in general do not achieve as good results as methods that do not consider appearance which represent static information [23]. Research by [24] assumed that subjects walk with constant speed without considering any covariate factors. The work only use static gait parameters like height, the length of upper and lower limbs and step length without including any dynamic features data thus the recognition rate achieved was only 85.1% when considering all static features. Ball *et al.* [25] investigated the possibility of recognizing people by using only the lower limb joint angles as its dynamic features. The dynamic feature is not fully utilized for the recognition task as the work only use standard deviation of joint trajectories which resulted in 74% recognition rate. As opposed to these works, gait recognition should integrate as much gait information as possible considering that body biometrics includes both static and dynamic features. Therefore, combining these features will increase the gait recognition performance significantly.

Currently there are gait fusion researches concerning 2D and 3D datasets that combine static and dynamic features. Although interests in gait biometrics continue to increase, only few approaches fused 3D static and dynamic features data. This is perhaps due to the complexity of extracting static and dynamic features at the same time and lack of publicly available 3D gait dataset [1]. The feature level fusion requires well prepared data in order to provide richer information of features from biometric data. Researches on gait fusion [26], [27], [28], [29], [30] utilized gait energy image (GEI) and silhouette 2D data indicated the difficulties in achieving significant results because of the problems in pre-processing data. Some of the schemes [31], [32] did not include the dimensionality reduction process which leads to the curse of dimensionality problem. Although fusion of features is accomplished, work by [33] highlighted that by including covariate factors, the recognition performance of gait biometric can be improved. Ismail *et al.* [34] fused only the silhouette frame size and the number of silhouette frame, without considering the important features of the silhouette images hence resulted in low recognition performance. The static and dynamic features are used based on mode-based approach in [35] but the results achieved were less impressive due to the small number of features are considered. The fusion work by [36] used model-based approach in extracting static features and dynamic features. But the results were not significant due to insufficient samples of data. They also emphasized that more sophisticated classification algorithms need to be applied in order to achieve better recognition rate.

1.2 Problem Statement

Many recognition schemes have been proposed for different types of gait data. Although silhouette 2D model free approach has previously achieved significant recognition rate, this approach depends much on the subject's appearance. Based on the influences of several previously mentioned covariate factors of human gait in real life scenarios, the effects of different covariate factors of gait recognition including walking speed and footwear, need to be explored and analysed. These covariate factors are highlighted since they represent the major covariate factors that affect gait recognition performance which practically represent real life environment, hence involves extra attention [5]. A 3D model-based gait approach is used in order to avoid the 2D silhouette distortion arising from viewpoint or segmentation error. The advantages of 3D model-based is that it allows for efficient and consistent features extraction from a human skeleton data hence, increasing the potential of finding significantly unique features of human gait [37].

To obtain optimal and reliability of biometric recognition performance, an automatic person recognition system should integrate as many informative clues as possible [38, 39]. Existing researches in gait recognition are either extracting static or dynamic features only for personal recognition. Moreover, despite the various properties of gait that might serve as recognition features, the previous works on gait recognition mainly adopted low level information such as 2D silhouette data as static data or use temporal features of joint angle as dynamic data separately. There are efforts to combine these features but most researches adopted 2D silhouette data which suffers from background noise and occlusion. Most approaches do not consider or combine the 3D static and dynamic gait features for personal recognition. Based on the idea that body biometrics include both the appearance of human body and the dynamic of gait motion measured during walking, some efforts are made to fuse the different sources of information available from 3D gait skeleton information for personal recognition. Fusion of 3D static and dynamic features across different covariate factors will increase the recognition performance of gait biometric recognition.

1.3 Research Questions

The ultimate goal of this research is to determine if it can distinguish a person based on fusion of static and dynamic features. The output of this research is expected to increase the recognition rate. The following research questions are formulated to address the stated general research question and the discussed problems in this research area:

i. **RQ1**: What are the covariate factors that affect the gait recognition performance?
ii. **RQ2**: Which gait features provide more accuracy for personal recognition?
iii. **RQ3**: Does fusing the classification output help improve the recognition?
iv. **RQ4**: How to evaluate the accuracy of the proposed approach in order to recognize a person based on gait?

1.4 Objectives of the Study

The objectives of this study have been derived from the problem statement above. The objectives of this research are:

i. To examine the effect of covariate factors on gait recognition performance;
ii. To create 3D static and dynamic gait features dataset for personal gait recognition;
iii. To propose an improved fusion technique for personal gait biometrics recognition; and
iv. To evaluate the quality of the proposed approach based on specific and acceptable benchmarks.

1.5 Scopes of the Study

The underlined research covers several areas that include gait biometric analysis approaches, feature extraction, feature selection, classification, fusion and evaluation. In order to achieve the objectives of the study, the research directions are limited to the following scope of study:

i. Microsoft Kinect Systemis is used to capture the gait motion data in 3D model-based format;
ii. Sample collection of gait motion data are collected by conducting a lab experiment based on Microsoft Kinect system at Mix and Virtual Environment Lab (MiViELab) employed by Universiti Teknologi Malaysia;
iii. The gait motion is focused at lower limb, that is the distance between pelvis and feet; and
iv. The proposed scheme is implemented using the MATLAB programme for feature extraction and feature selection, classification and some parts of fusion were done using Weka machine learning toolkit.

1.6 Significance of the Study

The result of this research would prominently contribute to gait recognition scheme for personal recognition. The contributions of this research are:

i. A fusion scheme for static and dynamic gait features data is developed to effectively identify a person based on the available and influential information of human body appreance and the dynamics of gait motion from human motion recordings.
ii. A comparative study of gait covariate factors with static and dynamic features can help in better understanding of the gait process in biometric recognition.
iii. The accuracy of classifications performance improved significantly when reducing dimensionality of 3D gait data.
iv. The recognition performance of the scheme can be enhanced by establishment of the fusion of static and dynamic feature data.

1.7 Thesis Outline

This thesis is divided into six chapters and organised as follows:

Chapter 1: This chapter introduce the purpose of gait biometric recognition and the background of the problem. From the problem statement, the whole problem of gait biometric can be understood and the objectives of this research specified.

Chapter 2: This chapter discusses the literature relevant to the research work. It begins with a description on the concepts of gait biometrics and gait analysis approaches. This is followed by a discussion and comparative evaluation on state-of-the-art gait biometric analysis issues and solution, feature selection, classification and fusion approaches. The comparative evolution from these four perspectives is necessary in order to understand the strengths and weaknesses of current approaches

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