View metadata, citation and similar papers at core.ac.uk

brought to you by CORE

provided by Universiti Teknologi Malaysia Institutional Repository

MODEL-BASED 3D GAIT BIOMETRIC USING QUADRUPLE FUSION CLASSIFIER

NOR SHAHIDAYAH BINTI RAZALI

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.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

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

LIST OF APPENDICES

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

REFERENCES

1. Ariyanto, G. and Nixon, M. S. Model-based 3D gait biometrics. *Proceedings of the Biometrics (IJCB), 2011 International Joint Conference on*. IEEE. 2011. 1-7.
2. Amin, T. and Hatzinakos, D. Determinants in human gait recognition. *Proceedings of the Electrical & Computer Engineering (CCECE), 2012 25th IEEE Canadian Conference on*. IEEE. 2012. 1-4.
3. Patrick, A. S. Fingerprint Concerns: Performance, Usability, and Acceptance of Fingerprint Biometric Systems. *National Research Council of Canada*. 2008.
4. Jain, A. K. and Kumar, A. Biometric recognition: an overview. In: ed. *Second Generation Biometrics: The Ethical, Legal and Social Context.* Springer. 49-79; 2012.
5. Kovač, J. and Peer, P. Human skeleton model based dynamic features for walking speed invariant gait recognition. *Mathematical Problems in Engineering*. 2014. 2014.
6. Nixon, M. Gait biometrics. *Biometric technology today*. 2008. 16(7): 8-9.
7. Cola, G., Avvenuti, M., Vecchio, A., Yang, G.-Z. and Lo, B. An unsupervised approach for gait-based authentication. *Proceedings of the Wearable and Implantable Body Sensor Networks (BSN), 2015 IEEE 12th International Conference on*. IEEE. 2015. 1-6.
8. Haque, A., Alahi, A. and Fei-Fei, L. Recurrent attention models for depth-based person identification. *Proceedings of the Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2016. 1229-1238.
9. Liu, Z. and Sarkar, S. Simplest representation yet for gait recognition: Averaged silhouette. *Proceedings of the Pattern Recognition, 2004. ICPR 2004. Proceedings of the 17th International Conference on*. IEEE. 2004. 211-214.

10. Sarkar, S., Phillips, P. J., Liu, Z., Vega, I. R., Grother, P. and Bowyer, K. W. The humanid gait challenge problem: Data sets, performance, and analysis. *IEEE transactions on pattern analysis and machine intelligence*. 2005. 27(2): 162-177.

11. Wang, Z., Sun, X., Sun, L. and Huang, Y. Manifold adaptive kernel semisupervised discriminant analysis for Gait recognition. *Advances in Mechanical Engineering*. 2013.

12. Lombardi, S., Nishino, K., Makihara, Y. and Yagi, Y. Two-point gait: decoupling gait from body shape. *Proceedings of the Proceedings of the IEEE International Conference on Computer Vision*. 2013. 1041-1048.

13. Lam, T. H., Cheung, K. H. and Liu, J. N. Gait flow image: A silhouette-based gait representation for human identification. *Pattern Recognition*. 2011. 44(4): 973-987.

14. Ahad, M. A. R., Tan, J. K., Kim, H. and Ishikawa, S. Motion history image: its variants and applications. *Machine Vision and Applications*. 2012. 23(2): 255-281.

15. Tanawongsuwan, R. and Bobick, A. Modelling the effects of walking speed on appearance-based gait recognition. *Proceedings of the Computer Vision and Pattern Recognition, 2004. CVPR 2004. Proceedings of the 2004 IEEE Computer Society Conference on*. IEEE. 2004. II-II.

16. Yoo, J.-H. and Nixon, M. S. Automated markerless analysis of human gait motion for recognition and classification. *Etri Journal*. 2011. 33(2): 259-266.

17. Yu, T. and Zou, J.-H. Automatic human Gait imitation and recognition in 3D from monocular video with an uncalibrated camera. *Mathematical Problems in Engineering*. 2012. 2012.

18. Lu, H., Plataniotis, K. N. and Venetsanopoulos, A. N. A full-body layered deformable model for automatic model-based gait recognition. *EURASIP Journal on Advances in Signal Processing*. 2008. 2008: 62.

19. Bouchrika, I. On Using Gait Biometrics for Re-Identification in Automated Visual Surveillance. *Developing Next-Generation Countermeasures for Homeland Security Threat Prevention*. 2016: 140.

20. Ahmed, M. H. and Sabir, A. T. Human Gender Classification Based on Gait Features Using Kinect Sensor. *Proceedings of the Cybernetics (CYBCON), 2017 3rd IEEE International Conference on*. IEEE. 2017. 1-5.

21. Guan, Y., Li, C.-T. and Roli, F. On reducing the effect of covariate factors in gait recognition: a classifier ensemble method. *IEEE transactions on pattern analysis and machine intelligence*. 2015. 37(7): 1521-1528.
22. Stone, E. E. and Skubic, M. Capturing habitual, in-home gait parameter trends using an inexpensive depth camera. *Proceedings of the Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE*. IEEE. 2012. 5106-5109.
23. Yang, K., Dou, Y., Lv, S., Zhang, F. and Lv, Q. Relative distance features for gait recognition with Kinect. *Journal of Visual Communication and Image Representation*. 2016. 39: 209-217.
24. Preis, J., Kessel, M., Werner, M. and Linnhoff-Popien, C. Gait recognition with kinect. *Proceedings of the 1st international workshop on kinect in pervasive computing*. New Castle, UK. 2012. P1-P4.
25. Ball, A., Rye, D., Ramos, F. and Velonaki, M. Unsupervised clustering of people from'skeleton'data. *Proceedings of the Proceedings of the seventh annual ACM/IEEE international conference on Human-Robot Interaction*. ACM. 2012. 225-226.
26. Chaubey, H., Hanmandlu, M. and Vasikarla, S. Enhanced view invariant gait recognition using feature level fusion. *Proceedings of the Applied Imagery Pattern Recognition Workshop (AIPR), 2014 IEEE*. IEEE. 2014. 1-5.
27. Nangtin, P., Kumhom, P. and Chamnongthai, K. Adaptive local module weight for feature fusion in gait identification. *Proceedings of the Intelligent Signal Processing and Communication Systems (ISPACS), 2016 International Symposium on*. IEEE. 2016. 1-4.
28. Hanmin, Y. and Peiliang, H. Gait recognition based on feature fusion and support vector machine. *Proceedings of the Online Analysis and Computing Science (ICOACS), IEEE International Conference of*. IEEE. 2016. 281-284.
29. Kawai, R., Makihara, Y., Hua, C., Iwama, H. and Yagi, Y. Person re-identification using view-dependent score-level fusion of gait and color features. *Proceedings of the Pattern Recognition (ICPR), 2012 21st International Conference on*. IEEE. 2012. 2694-2697.
30. Nandini, C., Sindhu, K. and Kumar, C. R. Gait recognition by combining wavelets and geometrical features. *Proceedings of the Intelligent Agent and*

Multi-Agent Systems (IAMA), 2011 2nd International Conference on. IEEE. 2011. 52-56.

31. Sivarathinabala, M. and Abirami, S. Automatic identification of person using fusion of gait features. *Proceedings of the Science Engineering and Management Research (ICSEMR), 2014 International Conference on*. IEEE. 2014. 1-5.
32. Jia, N., Sanchez, V., Li, C. T. and Mansour, H. On Reducing the Effect of Silhouette Quality on Individual Gait Recognition: A Feature Fusion Approach. *Proceedings of the 2015 International Conference of the Biometrics Special Interest Group (BIOSIG)*. 9-11 Sept. 2015. 2015. 1-5.
33. Makihara, Y., Muramatsu, D., Iwama, H. and Yagi, Y. On combining gait features. *Proceedings of the Automatic Face and Gesture Recognition (FG), 2013 10th IEEE International Conference and Workshops on*. IEEE. 2013. 1-8.
34. Ismail, S. N. S. N., Ahmad, M. I., Isa, M. N. M. and Anwar, S. A. Combination of gait multiple features at matching score level. *Proceedings of the Electronic Design (ICED), 2016 3rd International Conference on*. IEEE. 2016. 458-463.
35. Wang, Y., Sun, J., Li, J. and Zhao, D. Gait recognition based on 3D skeleton joints captured by kinect. *Proceedings of the Image Processing (ICIP), 2016 IEEE International Conference on*. IEEE. 2016. 3151-3155.
36. Derlatka, M. and Bogdan, M. Fusion of static and dynamic parameters at decision level in human gait recognition. *Proceedings of the International Conference on Pattern Recognition and Machine Intelligence*. Springer. 2015. 515-524.
37. Aggarwal, J. K. and Xia, L. Human activity recognition from 3d data: A review. *Pattern Recognition Letters*. 2014. 48: 70-80.
38. Kuncheva, L. I. *Combining pattern classifiers: methods and algorithms*. John Wiley & Sons. 2004
39. Veres, G. V., Nixon, M. S. and Carter, J. N. Model-based approaches for predicting gait changes over time. *Proceedings of the Intelligent Sensors, Sensor Networks and Information Processing Conference, 2005. Proceedings of the 2005 International Conference on*. IEEE. 2005. 325-330.

40. Murray, M. P. GAIT AS A TOTAL PATTERN OF MOVEMENT: INCLUDING A BIBLIOGRAPHY ON GAIT. *American Journal of Physical Medicine & Rehabilitation*. 1967. 46(1): 290-333.
41. Cutting, J. E. and Kozlowski, L. T. Recognizing friends by their walk: Gait perception without familiarity cues. *Bulletin of the psychonomic society*. 1977. 9(5): 353-356.
42. Cunado, D., Nixon, M. S. and Carter, J. N. Automatic extraction and description of human gait models for recognition purposes. *Computer Vision and Image Understanding*. 2003. 90(1): 1-41.
43. Winter, D. A. Overall principle of lower limb support during stance phase of gait. *Journal of biomechanics*. 1980. 13(11): 923-927.
44. Andrews, M., Noyes, F. R., Hewett, T. E. and Andriacchi, T. P. Lower limb alignment and foot angle are related to stance phase knee adduction in normal subjects: a critical analysis of the reliability of gait analysis data. *Journal of orthopaedic research*. 1996. 14(2): 289-295.
45. Shultz, S., Houglum, P. and Perrin, D. *Examination of Musculoskeletal Injuries with Web Resource*. Human Kinetics. 2015
46. Neumann, D. A. *Kinesiology of the musculoskeletal system: foundations for rehabilitation*. Elsevier Health Sciences. 2013
47. Sigal, L., Balan, A. O. and Black, M. J. Humaneva: Synchronized video and motion capture dataset and baseline algorithm for evaluation of articulated human motion. *International journal of computer vision*. 2010. 87(1-2): 4.
48. Hediyeh, H., Sayed, T., Zaki, M. H. and Mori, G. Pedestrian gait analysis using automated computer vision techniques. *Transportmetrica A: Transport Science*. 2014. 10(3): 214-232.
49. Herman, T., Mirelman, A., Giladi, N., Schweiger, A. and Hausdorff, J. M. Executive control deficits as a prodrome to falls in healthy older adults: a prospective study linking thinking, walking, and falling. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*. 2010: glq077.
50. Viccaro, L. J., Perera, S. and Studenski, S. A. Is timed up and go better than gait speed in predicting health, function, and falls in older adults? *Journal of the American Geriatrics Society*. 2011. 59(5): 887-892.

51. Noehren, B., Scholz, J. and Davis, I. The effect of real-time gait retraining on hip kinematics, pain and function in subjects with patellofemoral pain syndrome. *British journal of sports medicine*. 2010: bjsports69112.
52. Wren, T. A., Gorton, G. E., Ounpuu, S. and Tucker, C. A. Efficacy of clinical gait analysis: A systematic review. *Gait & posture*. 2011. 34(2): 149-153.
53. Chang, F. M., Rhodes, J. T., Flynn, K. M. and Carollo, J. J. The role of gait analysis in treating gait abnormalities in cerebral palsy. *Orthopedic Clinics of North America*. 2010. 41(4): 489-506.
54. Nixon, M. S. and Carter, J. N. Automatic recognition by gait. *Proceedings of the IEEE*. 2006. 94(11): 2013-2024.
55. Muaaz, M. and Mayrhofer, R. An analysis of different approaches to gait recognition using cell phone based accelerometers. *Proceedings of the Proceedings of International Conference on Advances in Mobile Computing & Multimedia*. ACM. 2013. 293.
56. Zhang, M. and Sawchuk, A. A. USC-HAD: a daily activity dataset for ubiquitous activity recognition using wearable sensors. *Proceedings of the Proceedings of the 2012 ACM Conference on Ubiquitous Computing*. ACM. 2012. 1036-1043.
57. Hoang, T., Nguyen, T. D., Luong, C., Do, S. and Choi, D. Adaptive Cross-Device Gait Recognition Using a Mobile Accelerometer. *JIPS*. 2013. 9(2): 333.
58. Muro-de-la-Herran, A., Garcia-Zapirain, B. and Mendez-Zorrilla, A. Gait analysis methods: An overview of wearable and non-wearable systems, highlighting clinical applications. *Sensors*. 2014. 14(2): 3362-3394.
59. Do, T. N. and Suh, Y. S. Gait analysis using floor markers and inertial sensors. *Sensors*. 2012. 12(2): 1594-1611.
60. Boulgouris, N. V., Hatzinakos, D. and Plataniotis, K. N. Gait recognition: a challenging signal processing technology for biometric identification. *IEEE Signal Processing Magazine*. 2005. 22(6): 78-90.
61. Choudhury, S. D. and Tjahjadi, T. Silhouette-based gait recognition using Procrustes shape analysis and elliptic Fourier descriptors. *Pattern Recognition*. 2012. 45(9): 3414-3426.
62. Zeng, W., Wang, C. and Yang, F. Silhouette-based gait recognition via deterministic learning. *Pattern Recognition*. 2014. 47(11): 3568-3584.

63. Iwama, H., Okumura, M., Makihara, Y. and Yagi, Y. The ou-isir gait database comprising the large population dataset and performance evaluation of gait recognition. *IEEE Transactions on Information Forensics and Security*. 2012. 7(5): 1511-1521.

64. Hadid, A., Ghahramani, M., Kellokumpu, V., Pietikäinen, M., Bustard, J. and Nixon, M. Can gait biometrics be spoofed? *Proceedings of the Pattern Recognition (ICPR), 2012 21st International Conference on*. IEEE. 2012. 3280-3283.

65. Wang, L., Tan, T., Ning, H. and Hu, W. Silhouette analysis-based gait recognition for human identification. *IEEE transactions on pattern analysis and machine intelligence*. 2003. 25(12): 1505-1518.

66. Kang, W. and Deng, F. Research on intelligent visual surveillance for public security. *Proceedings of the Computer and Information Science, 2007. ICIS 2007. 6th IEEE/ACIS International Conference on*. IEEE. 2007. 824-829.

67. Derawi, M. and Bours, P. Gait and activity recognition using commercial phones. *computers & security*. 2013. 39: 137-144.

68. Capela, N., Lemaire, E., Baddour, N., Rudolf, M., Goljar, N. and Burger, H. Evaluation of a smartphone human activity recognition application with able-bodied and stroke participants. *Journal of neuroengineering and rehabilitation*. 2016. 13(1): 5.

69. Rane, S. Standardization of biometric template protection. *IEEE MultiMedia*. 2014. 21(4): 94-99.

70. Georgescu, D. A Real-Time Face Recognition System Using Eigenfaces. *Journal of Mobile, Embedded and Distributed Systems*. 2011. 3(4): 193-204.

71. Amin, T. *Dynamic descriptors in human gait recognition*. University of Toronto; 2013

72. Tripathi, K. A comparative study of biometric technologies with reference to human interface. *International Journal of Computer Applications*. 2011. 14(5): 10-15.

73. Bolle, R. M., Connell, J., Pankanti, S., Ratha, N. K. and Senior, A. W. *Guide to biometrics*. Springer Science & Business Media. 2013

74. Powers, D. M. Evaluation: from precision, recall and F-measure to ROC, informedness, markedness and correlation. 2011.

75. Kale, A., Sundaresan, A., Rajagopalan, A., Cuntoor, N. P., Roy-Chowdhury, A. K., Kruger, V. and Chellappa, R. Identification of humans using gait. *IEEE Transactions on Image Processing*. 2004. 13(9): 1163-1173.

76. Jain, A., Flynn, P. and Ross, A. A. *Handbook of biometrics*. Springer Science & Business Media. 2007

77. Johansson, G. Visual perception of biological motion and a model for its analysis. *Perception & psychophysics*. 1973. 14(2): 201-211.

78. Tian, Y., Ben, X., Zhang, P. and Sun, M. Multilinear mean component analysis for gait recognition. *Proceedings of the Control and Decision Conference (2014 CCDC), The 26th Chinese*. IEEE. 2014. 2632-2637.

79. Bashir, K., Xiang, T. and Gong, S. Gait recognition without subject cooperation. *Pattern Recognition Letters*. 2010. 31(13): 2052-2060.

80. Man, J. and Bhanu, B. Individual recognition using gait energy image. *IEEE transactions on pattern analysis and machine intelligence*. 2006. 28(2): 316-322.

81. Muramatsu, D., Iwama, H., Makihara, Y. and Yagi, Y. Multi-view multi-modal person authentication from a single walking image sequence. *Proceedings of the Biometrics (ICB), 2013 International Conference on*. IEEE. 2013. 1-8.

82. Hosseini, N. K. and Nordin, M. J. Human gait recognition: A silhouette based approach. *Journal of Automation and Control Engineering*. 2013. 1(2): 259-267.

83. Kar, A. and Deb, K. Moving cast shadow detection and removal from Video based on HSV color space. *Proceedings of the Electrical Engineering and Information Communication Technology (ICEEICT), 2015 International Conference on*. IEEE. 2015. 1-6.

84. Nandy, A., Bhowmick, S., Chakraborty, P. and Nandi, G. C. Gait Biometrics: An Approach to Speed Invariant Human Gait Analysis for Person Identification. *Proceedings of the Proceedings of the Second International Conference on Soft Computing for Problem Solving (SocProS 2012), December 28-30, 2012*. Springer. 2014. 729-737.

85. Nixon, M. S., Tan, T. and Chellappa, R. *Human identification based on gait*. Springer Science & Business Media. 2010

86. Bouchrika, I., Goffredo, M., Carter, J. N. and Nixon, M. S. Covariate analysis for view-point independent gait recognition. *Proceedings of the International Conference on Biometrics*. Springer. 2009. 990-999.

87. Guan, Y., Wei, X., Li, C.-T. and Keller, Y. People identification and tracking through fusion of facial and gait features. *Proceedings of the International Workshop on Biometric Authentication*. Springer. 2014. 209-221.

88. Guan, Y. and Li, C.-T. A robust speed-invariant gait recognition system for walker and runner identification. *Proceedings of the Biometrics (ICB), 2013 International Conference on*. IEEE. 2013. 1-8.

89. Doi, T., Shimada, H., Makizako, H., Tsutsumimoto, K., Uemura, K., Anan, Y. and Suzuki, T. Cognitive function and gait speed under normal and dual-task walking among older adults with mild cognitive impairment. *BMC neurology*. 2014. 14(1): 67.

90. Tsuji, A., Makihara, Y. and Yagi, Y. Silhouette transformation based on walking speed for gait identification. *Proceedings of the Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on*. IEEE. 2010. 717-722.

91. Hossain, M. A., Makihara, Y., Wang, J. and Yagi, Y. Clothing-invariant gait identification using part-based clothing categorization and adaptive weight control. *Pattern Recognition*. 2010. 43(6): 2281-2291.

92. Qu, X. and Yeo, J. C. Effects of load carriage and fatigue on gait characteristics. *Journal of biomechanics*. 2011. 44(7): 1259-1263.

93. Bouchrika, I. and Nixon, M. S. Exploratory factor analysis of gait recognition. *Proceedings of the Automatic Face & Gesture Recognition, 2008. FG'08. 8th IEEE International Conference on*. IEEE. 2008. 1-6.

94. Matovski, D. S., Nixon, M. S., Mahmoodi, S. and Carter, J. N. The effect of time on the performance of gait biometrics. *Proceedings of the Biometrics: Theory Applications and Systems (BTAS), 2010 Fourth IEEE International Conference on*. IEEE. 2010. 1-6.

95. Bouchrika, I. *Gait analysis and recognition for automated visual surveillance*. University of Southampton; 2008

96. Kumar, N., Kunju, N., Kumar, A. and Sohi, B. Active marker based kinematic and spatio-temporal gait measurement system using LabVIEW vision. 2010.

97. Collins, M. M., Scholar, M., Piazza, S. and Bansal, P. N., *Validation of a protocol for motion analysis*, 2003, Citeseer.

98. Prakash, C., Mittal, A., Kumar, R. and Mittal, N. Identification of spatio-temporal and kinematics parameters for 2-D optical gait analysis system using passive markers. *Proceedings of the Computer Engineering and Applications (ICACEA), 2015 International Conference on Advances in*. IEEE. 2015. 143-149.

99. Alnowami, M., Khan, A., Morfeq, A. H., Alothmany, N. and Hafez, E. A. Feasibility study of markerless gait tracking using kinect. *Life Science Journal*. 2014. 11(7).

100. Xu, X., McGorry, R. W., Chou, L.-S., Lin, J.-h. and Chang, C.-c. Accuracy of the Microsoft Kinect™ for measuring gait parameters during treadmill walking. *Gait & posture*. 2015. 42(2): 145-151.

101. Xia, L., Chen, C.-C. and Aggarwal, J. K. Human detection using depth information by kinect. *Proceedings of the Computer Vision and Pattern Recognition Workshops (CVPRW), 2011 IEEE Computer Society Conference on*. IEEE. 2011. 15-22.

102. Zhang, Z. Microsoft kinect sensor and its effect. *IEEE MultiMedia*. 2012. 19(2): 4-10.

103. Kaenchan, S., Mongkolnam, P., Watanapa, B. and Sathienpong, S. Automatic multiple kinect cameras setting for simple walking posture analysis. *Proceedings of the Computer Science and Engineering Conference (ICSEC), 2013 International*. IEEE. 2013. 245-249.

104. Milovanovic, M., Minovic, M. and Starcevic, D. Walking in colors: human gait recognition using Kinect and CBIR. *IEEE MultiMedia*. 2013. 20(4): 28-36.

105. Li, T., Putchakayala, P. and Wilson, M. 3D Object Detection with Kinect. *Cornell Univ., New York*. 2011.

106. Gianaria, E., Grangetto, M., Lucenteforte, M. and Balossino, N. Human classification using gait features. *Proceedings of the International Workshop on Biometric Authentication*. Springer. 2014. 16-27.

107. Andersson, V. O. and de Araújo, R. M. Person Identification Using Anthropometric and Gait Data from Kinect Sensor. *Proceedings of the AAAI*. 2015. 425-431.

108. Aksoy, S. and Haralick, R. M. Feature normalization and likelihood-based similarity measures for image retrieval. *Pattern Recognition Letters*. 2001. 22(5): 563-582.

109. Abdi, M. N., Khemakhem, M. and Ben-Abdallah, H. Off-line text-independent arabic writer identification using contour-based features. *International Journal of Signal and Image Processing*. 2010. 1(1): 4-11.

110. Han, J. *Data Mining: Concepts and Techniques*. Morgan Kaufmann Publishers Inc. 2005

111. Yu, L. and Liu, H. Efficient feature selection via analysis of relevance and redundancy. *Journal of machine learning research*. 2004. 5(Oct): 1205-1224.

112. Guyon, I. and Elisseeff, A. An introduction to variable and feature selection. *Journal of machine learning research*. 2003. 3(Mar): 1157-1182.

113. Dash, M. and Liu, H. Feature selection for classification. *Intelligent data analysis*. 1997. 1(1-4): 131-156.

114. Liu, H., Dougherty, E. R., Dy, J. G., Torkkola, K., Tuv, E., Peng, H., Ding, C., Long, F., Berens, M. and Parsons, L. Evolving feature selection. *IEEE Intelligent systems*. 2005. 20(6): 64-76.

115. Kumari, B. and Swarnkar, T. Filter versus wrapper feature subset selection in large dimensionality micro array: A review. 2011.

116. Kumar, V. and Minz, S. Feature Selection. *SmartCR*. 2014. 4(3): 211-229.

117. Saeys, Y., Inza, I. and Larrañaga, P. A review of feature selection techniques in bioinformatics. *bioinformatics*. 2007. 23(19): 2507-2517.

118. Nikam, S. S. A comparative study of classification techniques in data mining algorithms. *Orient J Comput Sci Technol*. 2015. 8(1): 13-19.

119. Kesavaraj, G. and Sukumaran, S. A study on classification techniques in data mining. *Proceedings of the Computing, Communications and Networking Technologies (ICCCNT), 2013 Fourth International Conference on*. IEEE. 2013. 1-7.

120. Kohavi, R. and Quinlan, J. R. Data mining tasks and methods: Classification: decision-tree discovery. *Proceedings of the Handbook of data mining and knowledge discovery*. Oxford University Press, Inc. 2002. 267-276.

121. Thangaraj, M. and Vijayalakshmi, C. Performance Study on Rule-based Classification Techniques across Multiple Database Relations. *International Journal of Applied Information Systems (IJAIS)–ISSN*. 2013: 2249-0868.

122. Dietterich, T. G., Wettschereck, D., Atkeson, C. G. and Moore, A. W. Memory-based methods for regression and classification. *Proceedings of the Proceedings of the 6th International Conference on Neural Information Processing Systems*. Morgan Kaufmann Publishers Inc. 1993. 1165-1166.

123. Van Den Bosch, A. and Daelemans, W. Do not forget: Full memory in memory-based learning of word pronunciation. *Proceedings of the Proceedings of the Joint Conferences on New Methods in Language Processing and Computational Natural Language Learning*. Association for Computational Linguistics. 1998. 195-204.

124. Larose, D. T. k-Nearest Neighbor Algorithm. *Discovering Knowledge in Data: An Introduction to Data Mining*. 2005: 90-106.

125. Sarle, W. S. Neural networks and statistical models. 1994.

126. Ivancevic, V. G. and Ivancevic, T. T. *Neuro-fuzzy associative machinery for comprehensive brain and cognition modelling*. Springer. 2007

127. Su, J. and Zhang, H. Full Bayesian network classifiers. *Proceedings of the Proceedings of the 23rd international conference on Machine learning*. ACM. 2006. 897-904.

128. Friedman, N., Geiger, D. and Goldszmidt, M. Bayesian network classifiers. *Machine learning*. 1997. 29(2-3): 131-163.

129. Cheng, J. and Greiner, R. Comparing Bayesian network classifiers. *Proceedings of the Proceedings of the Fifteenth conference on Uncertainty in artificial intelligence*. Morgan Kaufmann Publishers Inc. 1999. 101-108.

130. Hsu, C.-W., Chang, C.-C. and Lin, C.-J. A practical guide to support vector classification. 2003.

131. Sanderson, C. and Paliwal, K. K. Information fusion and person verification using speech and face information. *Research Paper IDIAP-RR*. 2002: 02-33.

132. Jain, A., Nandakumar, K. and Ross, A. Score normalization in multimodal biometric systems. *Pattern Recognition*. 2005. 38(12): 2270-2285.

133. Kittler, J., Hatef, M., Duin, R. P. and Matas, J. On combining classifiers. *IEEE transactions on pattern analysis and machine intelligence*. 1998. 20(3): 226-239.

134. Zhang, D. *Advanced pattern recognition technologies with applications to biometrics*. IGI Global. 2009

135. Chitroub, S. Classifier combination and score level fusion: concepts and practical aspects. *International Journal of Image and Data Fusion*. 2010. 1(2): 113-135.

136. Kuncheva, L. I., Whitaker, C. J., Shipp, C. A. and Duin, R. P. Limits on the majority vote accuracy in classifier fusion. *Pattern Analysis & Applications*. 2003. 6(1): 22-31.

137. Lau, C. W., Ma, B., Meng, H. M.-L., Moon, Y. S. and Yam, Y. Fuzzy logic decision fusion in a multimodal biometric system. *Proceedings of the INTERSPEECH*. 2004.

138. Chitroub, S., Houacine, A. and Sansal, B. Evidential reasoning-based classification method for remotely sensed images. *Proceedings of the International Symposium on Remote Sensing*. International Society for Optics and Photonics. 2002. 340-351.

139. Kohlas, J. and Monney, P.-A. *A mathematical theory of hints: An approach to the Dempster-Shafer theory of evidence*. Springer Science & Business Media. 2013

140. Gabel, M., Gilad-Bachrach, R., Renshaw, E. and Schuster, A. Full body gait analysis with Kinect. *Proceedings of the 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. Aug. 28 2012-Sept. 1 2012. 2012. 1964-1967.

141. Araujo, R. M., Graña, G. and Andersson, V. Towards skeleton biometric identification using the microsoft kinect sensor. *Proceedings of the Proceedings of the 28th Annual ACM Symposium on Applied Computing*. ACM. 2013. 21-26.

142. Gianaria, E., Balossino, N., Grangetto, M. and Lucenteforte, M. Gait characterization using dynamic skeleton acquisition. *Proceedings of the Multimedia Signal Processing (MMSP), 2013 IEEE 15th International Workshop on*. IEEE. 2013. 440-445.

143. Hofmann, M., Geiger, J., Bachmann, S., Schuller, B. and Rigoll, G. The TUM Gait from Audio, Image and Depth (GAID) database: Multimodal recognition of subjects and traits. *Journal of Visual Communication and Image Representation*. 2014. 25(1): 195-206.

144. Webster, K. E., Wittwer, J. E. and Feller, J. A. Validity of the GAITRite® walkway system for the measurement of averaged and individual step parameters of gait. *Gait & posture*. 2005. 22(4): 317-321.

145. Veres, G. V., Nixon, M. S., Middleton, L. and Carter, J. N. Fusion of dynamic and static features for gait recognition over time. *Proceedings of the Information Fusion, 2005 8th International Conference on*. IEEE. 2005. 7 pp.

146. Brekelmans, J. Brekel kinect. *Retrieved March*. 2012. 30: 2012.

147. Helwig, N. E., Hong, S., Hsiao-Wecksler, E. T. and Polk, J. D. Methods to temporally align gait cycle data. *Journal of biomechanics*. 2011. 44(3): 561-566.

148. Auvinet, E., Multon, F., Aubin, C.-E., Meunier, J. and Raison, M. Detection of gait cycles in treadmill walking using a Kinect. *Gait & posture*. 2015. 41(2): 722-725.

149. Sinha, A., Chakravarty, K. and Bhowmick, B. Person identification using skeleton information from kinect. *Proceedings of the Proc. Intl. Conf. on Advances in Computer-Human Interactions*. 2013. 101-108.

150. Roy, S. H., Wolf, S. L. and Scalzitti, D. A. *The Rehabilitation Specialist's Handbook*. F. A. Davis Company. 2013

151. Shu-xu, J., Wu, Z. and Zhi-yong, H. Segmenting Single Actions from Continuous Captured Motion Sequences. *Proceedings of the Computer Science and Information Engineering, 2009 WRI World Congress on*. IEEE. 2009. 85-89.

152. Razali, N. S. and Manaf, A. A. Gait recognition using motion capture data. *Proceedings of the Informatics and Systems (INFOS), 2012 8th International Conference on*. IEEE. 2012. MM-67-MM-71.

153. Papadopoulos, G. T., Axenopoulos, A. and Daras, P. Real-Time Skeleton-Tracking-Based Human Action Recognition Using Kinect Data. In: Gurrin, C., Hopfgartner, F., Hurst, W., Johansen, H., Lee, H. and O'Connor, N. ed. *MultiMedia Modeling: 20th Anniversary International Conference, MMM 2014, Dublin, Ireland, January 6-10, 2014, Proceedings, Part I.* Cham: Springer International Publishing. 473-483; 2014.

154. Josiński, H., Świtoński, A., Jędrasiak, K. and Kostrzewa, D. Human identification based on gait motion capture data. *Proceedings of the*

Proceedings of the 2012 International MultiConference of Engineers and Computer Scientists, IMECS. 2012.

155. Lu, E. Classification of Accelerometer Data using Weka. 2014.
156. Haron, A. *Requirement Engineering Best Practices for Malaysian Public Sector*. Universiti Teknologi Malaysia; 2014
157. Janecek, A., Gansterer, W. N., Demel, M. and Ecker, G. On the relationship between feature selection and classification accuracy. *FSDM*. 2008. 4: 90-105.
158. Tulyakov, S., Jaeger, S., Govindaraju, V. and Doermann, D. Review of classifier combination methods. In: ed. *Machine Learning in Document Analysis and Recognition.* Springer. 361-386; 2008.
159. Wang, L., Ning, H., Tan, T. and Hu, W. Fusion of static and dynamic body biometrics for gait recognition. *IEEE Transactions on circuits and systems for video technology*. 2004. 14(2): 149-158.
160. Bazin, A. I. and Nixon, M. S. Probabilistic combination of static and dynamic gait features for verification. *Proceedings of the Defense and Security*. International Society for Optics and Photonics. 2005. 23-30.
161. Toh, K.-A., Kim, J. and Lee, S. Biometric scores fusion based on total error rate minimization. *Pattern Recognition*. 2008. 41(3): 1066-1082.
162. DeCann, B. and Ross, A. Relating roc and cmc curves via the biometric menagerie. *Proceedings of the Biometrics: Theory, Applications and Systems (BTAS), 2013 IEEE Sixth International Conference on*. IEEE. 2013. 1-8.