International Journal of Engineering Technology Science and Research
IJETSR
www.ijetsr.com
ISSN 2394 – 3386
Volume 5, Issue 1
January 2018

An Overview of Gait Biometrics

Pramod Jagan Deore
R. C. Patel Institute of Technology, Shirpur (M. S.), INDIA
Sagar Arun More
R. C. Patel Institute of Technology, Shirpur (M. S.), INDIA

ABSTRACT

Recognizing human from a distance by gait biometric has attracted researchers in recent years. It has many advantages like; non-invasive, less obscured, un-obtrusive, without subject cooperation, from a distance, can work well with low quality video. Comparatively gait biometric is newer modality than face, iris and fingerprint. Gait recognition and analysis have been studied heavily in recent past. In this paper we present an overview of gait recognition. The approaches are broadly classified into model free, model based, view invariant, fusion of model free and model based.

Keywords

Gait, human recognition, model free, model based, view invariant.

INTRODUCTION

Gait is a potential biometric trait where unconstrained person identification is demanded. It is a protocol free biometric technique which does not require willingness of person and hence found application in surveillance. However, commonly used biometric recognition systems usually operate in constrained acquisition scenarios and under rigid protocols. The finger print, iris and face recognition could not be the right choice in the unconstrained environment, where distant data capture is required. Comparatively, gait comprised of motion trajectories of various body parts, have a potential to get captured properly from relatively far distance. Walking normally performed naturally as well. It doesn't need systematic data capture process, where subjects should necessarily be informed. This makes the identification process protocol free. The extended application of gait recognition can be suspectus identification in a sensitive area where security is at the highest priority. These characteristics of gait biometrics lead it to be an attractive modality from the perspective of human recognition at a distance. In spite of various advantages, co-variate factors like; walking speed, carrying conditions, clothing, the surface of walking, fatigue, drunkenness, pregnancy, injury to feet and the psycho-somatic condition affects the normal walking style. View angle also play vital role while testing such system. It may possible that certain view angle provides discriminant information of walking individual while another may not. Hence, an investigation is needed to find robust gait representation which can cope up with these challenges in multi-view scenario.

Biometrics is considered as one of the successful applications of pattern recognition and has been widely used in several domains, such as authentication in highly restricted areas, attendance record in office premises, citizenship identification-verification and in the field of forensics. These biometric systems are mostly based on modalities like fingerprint, iris and face. However, commonly used biometric recognition systems usually operate in constrained acquisition scenarios and under rigid protocols. This scenario motivates researchers to explore the development of non-cooperative systems [1]. In the bio-metrics application which requires distant data (sample) capture, it becomes almost impossible to acquire the samples, e.g. fingerprints or iris. Besides popular biometric modalities like fingerprint, face and iris; activity based biometrics [2] can add the value to the identification process. Especially, in the case of biometric applications where far distant data capture process is involved. In such scenario, gait is the useful biometric trait. The gait recognition is based on the activity of person, namely walking. The gait activity is the composition of motion trajectories and coordinated movements of the various body parts and mostly su er from the co-variate conditions. There are several advantages of the gait based person identification over the conventional biometrics such as:

1) Most suitable for non-cooperative and unconstrained bio-metric process.
2) Walking normally happen with subject without demanding from it and hence it's a natural sample.
3) Unlike face and iris, gait can be captured from multiple angle / views, which makes data acquisition more informative.
4) Even work well with low quality video data.
5) No fine details are required as in face, iris or finger print based recognition system.

Though, the gait recognition have been researched for long time, there are challenges such as:

1) In some situations like restaurants, shopping malls walking doesn't always happen.
2) In crowded places, walking can be done in restrictive manner, leading to a change in gait cycle and affecting bio-metric process negatively.
3) Particular place or situation may have predictable activity to be happened more frequently and hence can be exploited e.g. in college / department canteen, shaking hands and paying bill after taking out wallet can be more dominant activities.
4) Gait sample may not give accurate shape profiles with loose clothes.
5) Gait can be affected by various co-variate factors like speed, cloths, surface of walking, illness, drunkenness, pregnancy.
6) Viewing angle effect plays vital role in multi view system.

In the unconstrained environment and distant data capture based bio-metric system, fingerprint, iris and face recognition could not be right choice. Comparatively gait, comprised of motion trajectories of various body parts, have a potential to get captured properly from relatively far distance. It doesn't need systematic data capture process and only camera installation is required, where subjects are not necessarily be informed, which make the identification process protocol free.

GAIT RECOGNITION APPROACHES

Gait recognition and analysis have been studied heavily in recent past. In this section we will discuss briefly about it. The approaches in the literature can be broadly classified into two types viz. model free [3, 4, 5, 6] and model based [7, 8, 9, 10]. In these approaches, various static and dynamic features of gait sequences were extracted by using shape analysis, image geometry transformations, wavelet analysis, so on and so forth.

Model Free Approach: In the model free method, the features extracted directly from the image in the spatial domain. The very initial attempt to demonstrate the visual perception of motion patterns of human displacement by using moving light display is done by Johanson [11]. Whereas, [3, 12] extract shape based features by using Procrustes shape analysis for automatic gait recognition. In [13], the author proposed a 3D method which utilizes complete body shape signature. They extract stereo silhouette vector from 3D contour and transform it into 1D stereo gait feature. Gait is a cyclic motion due to dynamic body parts movement which yields spatio-temporal patterns. The spatio-temporal patterns of walking person have been also analyzed by wavelet analysis [14, 15]. In [14], radon transform is used as it guarantees maximum energy for most frequently changing silhouette area like legs and hands along with various joints. Further, Haar wavelet transform is used to extract horizontal and vertical features as these features represent upper and lower limb movement. Another wavelet based approach [15] uses time frequency analysis of extracted gait cycle. They calculate the area of lower half of silhouette image. The gait cycle is constructed by using the varying area of silhouette image half portion as the person walks. After wavelet decomposition, they calculate mean, standard deviation, skewness and kurtosis of each sub-band as features.

Goffredo et al. [16] computes gait volume using 3D moments. In their another works [17] and [18] they extract kinematical information such as; angles of hip, ankle, knee and positions of thigh and various body parts using anatomical measurements. Whereas, in [19], [20] spatio-temporal symmetry is used for human identification. The symmetry operator is applied on each edge map to obtain spatial symmetry map. In [19], sobel operator is used to obtain edge map. In [20], the symmetry operator is applied to optical flow to get symmetry maps. Further Fourier descriptor is obtained as gait signature from averaged symmetry maps.

Since past decade, most of the model free approaches use gait energy image (GEI) suggested by [21]. Bashir et al [22] developed supervised and unsupervised feature selection methods using GEI representation of gait sequences. Wrapper algorithm used in supervised feature selection and unsupervised feature selection includes computation of standard deviation of GEI intensity values at all the pixel locations across GEI templates. In [23], Gait Entropy Image (GEnI) is computed by calculating Shanon entropy for each pixel in silhouette image. The GEnI captures motion information and therefore robust to co-variate conditions. The method in [24], which is without subject cooperation, use GEnI representation for recognition of person in different co-variate conditions in which the probe and gallery set are the mix of all co-variates. Whereas, [25] extract features like; Motion Direction Image (MDI) and Motion Intensity Image (MII) through optical flow fields for person recognition. In [26], Conditional Sorting Local Binary Pattern (CS-LBP) is used to extract different blend direction images from GEI. Further, they calculate recognition ability, which is the ratio of between class distance and within class distance of these blend features for eight sorting directions. They fuse these features to form an augmented feature which further used for recognition. In a recent GEI based method [27], horizontal motion estimated by computing Shanon entropy of each row of GEI. Further, group Lasso learning algorithm is used to segment the motion based vector into blocks of similar motion values. The body part, which has highest average motion vector value is selected as a feature vector.

For model free gait recognition approach, GEI has been proved as a simple and effective representation. It performs well for non-covariate conditions well and sensitive to co-variate factors like clothing and carrying conditions. To overcome these problems, variants of GEI have been presented such as; Enhanced GEI, Active Energy Image, Gait Entropy Image etc. Still their average recognition rates are not promising. This is might be because of inclusion of some body parts which contribute negative recognition ability. To remove such body parts Pratheepan et al [28], [29] used Poisson Random Walking technique. Similar approach is presented by [30], in which the whole human body (GEnI) is divided into small parts having size of a single row. They computed rank 1 recognition rate from bottom row upto top row by merging immediate upper row into last row. Using this method they identified body parts which has negative contribution in recognition. Such body parts excluded or removed and only the body parts with positive contribution are used for overall recognition.

Recently Xu [31] and Li [32] presented different variants of GEI in the regard of co-variates like clothing and speed. In [32], Gait Energy Response Function (GERF) is used which is eigen vector corresponding to largest eigen value. It transforms an original GEI into more discriminative form under cloth co-variate condition. Whereas, [31] transform GEI into Single Support GEI (SSGEI) representation. The SSGEI further convolved with Gabor Filter. All the Gabor filtered images are then aligned to represent the final gait feature under speed co-variate condition.

In [3], Procrustes Shape Analysis is used to represent gait signature, which is obtained by extracting mean shape of unwrapped silhouette. Whereas, [4] is a 3D approach for gait recognition, which construct 3D silhouette vector of 2D scene by using stereo vision method. In a recent work [6], complete canonical correlation analysis is used to compute correlation between two GEI features. In another recent paper [5], author extract different width vectors and combined them to construct gait signature. This feature then approximated by RBF network for recognition.

Model Based Approach: In the model based approach, the human walking mechanism is modeled by some mathematical or kinematical model such as pendulum, ellipse etc. The model parameters are extracted to represent human shape and motion. Hence, gait models can either shape model or motion model. The advantage of model based approach is it can handle occlusion quite well. It is also scale and rotation invariant as opposed to model free approach.

An initial model based attempt for gait recognition in spatio-temporal (XYT) volume is done by Niyogi and Adelson [7]. First, they found the bounding contours of the walker by fitting it with snakes. A simplified 5-stick model which is controlled by these contours then used. A characteristic gait pattern in XYT is generated from the model parameters like angle signals from the complete sequence for recognition.

The method presented in [8], combine several features like area, gravity centre and orientation. Here, they calculate similarity distance of each feature separately and then different normalized distances combined together to obtain total distance. Whereas, [9] modeled gait cycle as a chain of key poses and extracted pose energy image feature. The key poses were estimated by K-means clustering of all the PCA transformed silhouettes across gait cycle. The state transition model is used to form the chain of estimated key poses.

In [33], the bulk motion, shape and articulated motion estimation was done by gait motion model adaptation. Motion compensated temporal accumulation algorithm is used to determine the bulk motion. They modeled head, torso by ellipse and legs by line segments. Modeling the gait by Fourier series has been proved as most successful [34, 35, 36, 37]. In [34, 35], first the various joint angles are estimated and then view normalization is done for any arbitrary view angle into saggital plane. The motion information is derived by using Elliptic Fourier Descriptors. In [36] the leg is modeled as two pendula joined in series which exhibit oscillatory behavior. The gait signature is obtained from phase weighted magnitude of the lower order Fourier components of thigh and knee rotation. Yoo et al [38, 39, 40] used a 2D-stick model to represent human. They used trigonometric polynomial interpolant functions to analyze the periodic motion of human. Various body points such as; hip, knee, thigh are estimated using anatomical measurements. The joint angles of such body points then computed for obtaining kinematic information.

Recent development in model based gait recognition emphasizes modeling the multi-view gait sequences by using view normalization techniques. Worapan et al [41, 42, 43, 44] use View Transformation Model (VTM) to normalize probe and gallery view in the same direction. The method presented in [41] is SVD based VTM approach and [42] is SVR based. The problem like data redundancy in earlier methods improved in [43]. Whereas, [44] uses MLP to construct VTM model for multi-view and cross-view gait recognition.

Fusion Approach: Either static or dynamic feature alone can perform well for recognition but with some limitations. While dealing with static features, one cannot analyze dynamic features and vice-verse. Extracting both features simultaneously improve the recognition rate on the cost of increased computational complexity. Various approaches are proposed in this regard, which extract static and dynamic features simultaneously, either fusing model free and model based approaches [45, 12, 46, 47, 48] or fusing various features into a single augmented feature vector [49, 50, 51, 52].

In [49], gait energy image and motion energy images are combined to form feature vector, whereas in [50], the static silhouette template (SST) and dynamic silhouette template (DST) are fused to construct dynamic static silhouette template (DSST). The position of the gravity center of human body may change because of various co-variate factors as aforementioned. This problem is addressed by [51]. In this paper, authors divides the GEI transformed image into three body parts like; head, torso and leg. Further, they compute shifted energy image (SEI) features which are horizontal centers of body parts. Next, gait structural profile (GSP) extracted to capture body geometry. For this, silhouette segmented into four body parts as per the anatomical measurements like; head, torso, left and right leg. The GSP, which is the deference of gravity center of these segmented body parts and entire body is computed. These two features then used in combination for recognition. In [52], two distinct features namely frieze pattern, which preserves spatial information and wavelet coefficients, which preserves low frequency information are extracted. Factorial HMM is used to combine these features and parallel HMM facilitate decision level fusion of two individual classifiers for recognition. All these approaches signify that, the fusion of multiple gait features improves the recognition system performance.

There are certain methods, which explore static and dynamic characteristics of the human body. They fuse static and dynamic features for improvement in performance of gait recognition system. In [45], features like; centroid, armswing, stride length, mean height were extracted from the binary silhouette. Further, they fit ellipse on each region and compute it's aspect ratio and orientation. These features then combined and transformed by DCT and applied to generalized regression neural network for recognition. Whereas in [12], mean shape extracted by using Procrustes Shape Analysis as a static feature. The dynamic features extracted by modeling human body parts by truncated cone, head by sphere and computing joint angles of this model. A human skeleton model is adopted in [46] to extract dynamic features and computing various angles of key body points. The static feature denoted by wavelet descriptor, which is obtained by applying wavelet transform to the boundary-centroid distance.

In [53], HMMs are used to extract static and dynamic gait features, without using any human body model. The static features extracted by conventional HMM and dynamic features by hierarchical HMM. After labeling, they extract three features namely; component area, component center and component orientation. First HMM represents general shape information while the second HMM extracts detailed sub-dynamic information. Whereas in [54], Local Binary Pattern is used to denote the texture information of optical flow as the static feature. Dynamic feature represented by HMM with Gaussian mixture model. In [47], the GEI transformed by dual tree complex wavelet transform (DTCWT) with deferent scales and orientations. A two stage Gaussian mixture model denote the patch distribution of each DTCWT based gait image. Further, to model the correlation of multi-view gait feature, a sparse local discriminant canonical correlation model is used. In a recent paper [48], the dynamic feature extracted by Lucas-Kanade based optical flow image. The mean shape of head and shoulder then extracted by using Procrustes Shape Analysis, which is the static feature. The fusion is done on score level.

It has been noted that not all the aforementioned methods adopt human body model such as skeleton to extract dynamic features. Most often, authors prefer mathematical modeling, as it is efficient to extract deferent kinds of features and also facilitate lower computational complexity.

View-Invariant Approach: The view-invariant gait identification is relatively new approach. The most desirable property of this approach is to identify test subject walking at any arbitrary view angle. It uses either any one of two or both approaches as discussed before. i. e. model free or model based. In [55], a viewpoint independent method is proposed which require single camera without calibration and prior knowledge of subject/person pose. The test subject is identified by projecting the limb motion of subject which is walking at arbitrary view angle onto the lateral/side-view plane. First, they do marker less joint estimation followed by reconstruction method for viewpoint rectification. In [56], author has proposed a joint subspace learning method for view-invariant gait recognition. First, radon transform based energy images of sequences extracted and further they perform canonical correlation analysis to get representation coefficients, which they use as view-invariant features. Next, they obtain prototypes of various views by using PCA. The samples of different views represented as linear combination of these prototypes and then extract the coefficients which further used for recognition. Whereas in [57], author extract a gait texture image which preserve gait information of a particular view angle. Further, they apply transform invariant low rank textures to project gait information of arbitrary view on to sagittal plane. In a recent paper [48], gait flow image extracted by Lukas-Kanade method as dynamic feature, head and shoulder mean shape by Procrustes shape analysis as static feature. In identification phase, they compute view angle or walking direction of test subject along with the static and dynamic features. A simple Euclidean distance classifier is used to find similarity measure between test and gallery images.

CONCLUSION

Gait is behavioral characteristic that possess individual deference formed in course of human growth. Gait is all external appearance that consists of human body structure, motion regulating system, behavioral and psychological activities when person is walking. Compared with other biometrics, Gait requires no object contact and is measured at a distance. Hence, it is applied to passive vision surveillance scenario such as ranks, airports and military departments. However, gait is affected by various physiological, psychological and external factors such as footwear, clothing, surface of walking, mood, illness, fatigue, and so on.

Considerable work has been done in human gait recognition, still there are many challenges and scope to improve the system performance. Investigation is needed regarding various features which vary with individual. Correct classification rate is always being a problem with any biometric system. In gait recognition covariate factors can certainly bring down the recognition performance. Efficient methods to remove covariate factors and best discrimination among classes are required. Recognition rate for outdoor video data is low as compared to indoor video data and hence significant efforts have to be made on robust segmentation in case of outdoor video data. Development of more flexible model based method to solve the conflicts between model complexity and model descriptive capability is required. Though model free approaches are more feasible than model based, fusion of model based and model free approaches can yields better results because of increased feature space and capability to fit model for feature extraction. Most of the work that have been reported in the literature is mainly concentrated on recognizing subject which makes a fixed angle with the camera, but the more efforts have to be made to develop the system which will recognize subject from the information obtained from multi - view angles.

REFERENCES

[1] M. Savvides, K. Ricanek, D. L. Woodard, G. Dozier, Unconstrained Biometric Identification: Emerging Technologies, *Computer (*43) (2010) 56–62.

[2] A. Iosifidis, A. Tefas, I. Pitas, Activity-Based Person Identification using Fuzzy Representation and Discriminant Learning, *IEEE Transactions on Information Forensics and Security* 7 (2) (2012) 530–542.

[3] Liang Wang, Tieniu Tan, Weiming Hu, Huazhong Ning, Automatic Gait Recognition Based on Statistical Shape Analysis, *IEEE Transactions on Image Processing* 12 (9) (2003) 1120–1131.

[4] H. Liu, Y. Cao, Z. Wang, Automatic Gait Recognition From A Distance, *In Proc. Chinese Control and Decision Conference, CCDC* (2010) 2777–2782.

[5] W. Zeng, C. Wang, View- Invariant Gait Recognition Via Deterministic Learning, *Neurocomputing, Elsevier B.V.* (175) (2016) 324–335.

[6] T. Y. Z. L. Xianglei Xing, Kejun Wang, Complete Canonical Correlation Analysis With Application to Multi-View Gait Recognition, *Pattern Recognition, Elsevier B. V.* (50) (2016) 107–117.

[7] S. A. Niyogi, E. H. Adelson, Analyzing and Recognizing Walking Figures in XYT, *In Proc. Conference on Computer Vision and Pattern Recognition, CVPR* (1994) 469–474.

[8] X. Huang, N. V. Boulgouris, Model-based Human Gait Recognition Using Fusion of Features, *In Proc. IEEE International Conference on Acoustics Speech and Signal Processing* (2009) 1469–1472.

[9] A. Roy, S. Sural, J. Mukherjee, A Hierarchical Method Combining Gait and Phase of Motion With Spatiotemporal Model For Person Re-Identification, *Pattern Recognition Letters* 33 (14) (2012) 1891–1901.

[10] J. N. C. Michela Goffredo, Imed Bouchrika, M. S. Nixon, Self-Calibrating View-Invariant Gait Biometrics, *IEEE Transactions on Systems, Man and Cybernetics - Part B: Cybernetics* 40 (4) (2010) 997–1008.

[11] G. Johansson, Visual Perception of Biological Motion and a Model for it's Analysis, *Perception and Psychophysics* 14 (2) (1973) 210–211.

[12] L. Wang, H. Ning, T. Tan, W. Hu, Fusion of Static and Dynamic Body Bio metrics for Gait Recognition, *IEEE Transactions on Circuits and Systems for Video Technology* 14 (2) (2004) 149–158.

[13] H. Liu, Y. Cao, Z. Wang, A Novel Algorithm of Gait Recognition, *In Proc. International Conference on Wireless Communications and Signal Processing* (2009) 1–5.

[14] H. Zhang, Z. Liu, Gait Representation and Recognition Using Haar Wavelet and Radon Transform, *In Proc. WASE International Conference on Information Engineering* 1 (2009) 83–86.

[15] T. Amin, D. Hatzinakos, Wavelet Analysis of Cyclic Human Gait For Recognition, *In proc. 16 th International Conference on Digital Signal Processing* (2009) 1–6.

[16] M. Goffredo, J. N. Carter, M. S. Nixon, Front-view Gait Recognition *2nd IEEE International Conference on Biometrics: Theory, Applications and Systems, 2008. BTAS* 2008.

[17] M. Goffredo, I. Bouchrika, J. Carter, M. Nixon, Performance Analysis for Gait in Camera Networks, *Proceeding of the 1st ACM workshop on Anal ysis and retrieval of events actions and work flows in video streams AREA 08* (2008) 73.

[18] M. Go redo, J. N. Carter, M. S. Nixon, 2D Markerless Gait Analysis, *4th European Conference of the International Federation for Medical and Biological Engineering* 22 (2009) 67–71.

[19] J. B. Hayfron-Acquah, M. S. Nixon, J. N. Carter, Human identification by spatio-temporal symmetry, *Proceedings - International Conference on Pattern Recognition* 16 (1) (2002) 632–635.

[20] J. B. Hayfron-Acquah, M. S. Nixon, J. N. Carter, Automatic gait recognition by symmetry analysis, *Pattern Recognition Letters* 24 (13) (2003) 2175–2183.

[21] J. Han, B. Bhanu, Individual Recognition Using Gait Energy Image., *IEEE Transactions on Pattern Analysis and Machine Intelligence* 28 (2) (2006) 316–322.

[22] S. G. Khalid Bashir, Tao Xiang, Feature Selection on Gait Energy Image for Human Identification, *In Proc. IEEE International Conference on Acoustics, Speech and Signal Processing* (ICASSP-2008) (2008) 985–988.

[23] S. G. Khalid Bashir, Tao Xiang, Gait Recognition Using Gait Entropy Image, *In Proc. 3rd International Conference on Crime Detection and Prevention (ICDP-2009)* (2009) 985–988.

[24] S. G. Khalid Bashir, Tao Xiang, Gait Representation Using Flow Fields, *In Proc. British Machine Vision Conference (BMVC)* (2009) 1–11.

[25] S. G. Khalid Bashir, Tao Xiang, Gait Recognition without Subject Cooperation, *Pattern Recognition Letters* 31 (2010) 2052–2060.

[26] Y.-J. D. Chih-Hsien Hsia, Jen-Shiun Chiang, T.-A. Lin, Conditional Sorting Local Binary Pattern Based on Gait Energy Image for Human Identification, *In Proc. International Conference on Image Processing, Computer Vision and Pattern Recognition*. 2013

[27] G. M. Imad Rida, Xudong Jiang, Human Body Part Selection by Group Lasso of Motion for Model-Free Gait Recognition , *IEEE Signal Processing Letters* 23 (1) (2016) 154–158.

[28] P. Yogarajah, J. V. Condell, G. Prasad, PRW GEI : Poisson Random Walk based Gait Recognition, *In 7th International Symposium on Image and Signal Processing and Analysis* (2011) 662-667.

[29] P. Yogarajah, J. V. Condell, G. Prasad, Analysis of most important parts for silhouette-based gait recognition, *Machine Vision and Image Processing Conference (IMVIP)*, (2011) 103-104..

[30] R. S. Islam, Effective Part-Based Gait Identification Using Frequency-Domain Gait Entropy Features, *Multimedia Tools and Applications* 74 (9), (2015) 3099–3120.

[31] C. Xu, Y. Makihara, X. Li, Y. Yagi, J. Lu, Speed Invariance vs . Stability : Cross-Speed Gait Recognition Using Single-Support Gait Energy Image, *Asian Conference on Computer Vision*, (2016) 1–16.

[32] X. Li, Y. Makihara, C. Xu, D. Muramatsu, Gait Energy Response Function for Clothing-invariant Gait Recognition, *Asian Conference on Computer Vision*, (2016) 257-272

[33] D. K. Wagg, M. S. Nixon, On Automated Model-based Extraction and Analysis of Gait, *In Proc. 6th IEEE International Conference on Automatic Face and Gesture Recognition* (2004) 11–16.

[34] Imed Bouchrika, Mark Nixon Markerless Feature Extraction for Gait Analysis, *Conference on Advances in Cybernetic Systems* (2006) 6.

[35] I. Bouchrika, M. Goffredo, J. N. Carter, M. S. Nixon, Covariate Analysis For View-Point Independent Gait Recognition, *Lecture Notes in Computer Sci ence (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 5558 LNCS* (2009) 990–999.

[36] C.-y. Yam, M. S. Nixon, J. N. Carter, Extended Model-Based Automatic Gait Recognition of Walking and Running, *AVBPA* (2001) 278–283.

[37] S. D. Mowbray, M. S. Nixon, Automatic Gait Recognition via Fourier Descriptors of Deformable Objects, *Audio and Video Based Biometric Person Authentication (2003)* 566–573.

[38] J.-H. Yoo, M. S. Nixon, Automated Markerless Analysis of Human Gait Motion for Recognition and Classification, *ETRI Journal* 33 (2) (2011) 259–266.

[39] J.-H. Yoo, M. S. Nixon, C. J. Harris, Extracting Gait Signatures based on Anatomical Knowledge, *In proc. BMVA A Symposium on Advancing Biometric Technologies* (2002) 596–606.

[40] J. H. Yoo, K. Y. Moon, D. Hwang, M. S. Nixon, Automated Human Recognition By Gait Using Neural Network, *1st International Workshops on Image Processing Theory, Tools and Applications, IPTA 2008*.

[41] H. L. Worapan Kusakunniran, Qiang Wu, J. Zhang1, Multiple Views Gait Recognition using View Transformation Model Based on Optimized Gait Energy Image , *In Proc. 12th IEEE International Conference on Computer Vision (2009)* 1058–1064.

[42] H. L. Worapan Kusakunniran, Qiang Wu, J. Zhang1, Support Vector Regression for Multi-View Gait Recognition based on Local Motion Feature Selection , In *Proc. IEEE Conference on Computer Vision and pattern Recognition (2010)* 974–981.

[43] H. L. Worapan Kusakunniran, Qiang Wu, J. Zhang1, Gait Recognition Under Various Viewing Angles Based on Correlated Motion Regression , *IEEE Transaction on Circuits and Systems for Video Technology* 22 (6) (2012) 966–980.

[44] H. L. Worapan Kusakunniran, Qiang Wu, J. Zhang, Cross-View And Multi View Gait Recognitions Based On View Transformation Model Using Multi Layer Perceptron , *Pattern Recognition Letters* 33 (7) (2012) 882–889.

[45] L. K. Luv Rustagi, G. N. Pillai, Human Gait Recognition Based on Dynamic and Static Features using Generalized Regression Neural Network, *Second International Conference on Machine Vision*, *IEEE Computer Society* (2009) 64–68.

[46] D. Ming, C. Zhang, Y. Bai, B. Wan, Y. Hu, K. Luk, Gait Recognition Based on Multiple Views Fusion of Wavelet Descriptor and Human Skeleton Model, *In Proc. IEEE International Conference on Virtual Environments, Human-Computer Interfaces and Measurement Systems (VECIMS)* (2009) 246–249.

[47] H. Hu, Multiview Gait Recognition Based on Patch Distribution Features and Uncorrelated Multilinear Sparse Local Discriminant Canonical Cor relation Analysis, *IEEE Transaction on Circuits and Systems for Video Technology* 24 (4) (2014) 617–630.

[48] L. W. Songmin Jia, X. Li, View-invariant Gait Authentication Based on Silhouette Contours Analysis and View Estimation, *IEEE/CAA Journal of Automatica Sinica* 2 (2) (2015) 226–232.

[49] S. Hong, H. Lee, E. Kim, Fusion of Multiple Gait Cycles for Human Identification, *In Proc. ICCAS-SICE* (2009) 3171–3175.

[50] J. C. Y. Pratheepan, G. Prasad, The use of Dynamic and Static Characteristics of Gait for Individual Identification, *13th Irish Machine Vision and Image Processing Conference*, *IEEE Computer Society* (2009) 111–116.

[51] N. V. B. Xiaxy Huang, Gait Recognition with Shifted Energy Image and Structural Feature Extraction, *IEEE Transactions on Image Processing* 21 (4) (2012) 2256–2268.

[52] H. Z. H. H. Changhong Chen, Jimin Liang, J. Tian, Factorial HMM and Parallel HMM for Gait Recognition, *IEEE Transaction on Systems, Man, and Cybernetics Part C: Applications and Reviews* 39 (1) (2009) 114–123.

[53] N. V. Boulgouris, X. Huang, Gait Recognition Using HMMs and Dual Discriminative Observations for Sub-Dynamics Analysis, *IEEE Transaction on Image Processing* 22 (9) (2013) 3636–3647.

[54] Z. Z. D. Z. Maodi Hu, Yunhong Wang, J. Little, Incremental Learning for Video-Based Gait Recognition With LBP Flow, *IEEE Transaction on Cybernetics* 43 (1) (2013) 77–89.

[55] M. Goffredo, I. Bouchrika, J. N. Carter, M. S. Nixon, Self-Calibrating View Invariant Gait Biometrics., *IEEE Transactions on Systems Man and Cybernetics: Part B Cybernetics* 40 (4) (2010) 997–1008.

[56] N. Liu, J. Lu, Y. P. Tan, Joint Subspace Learning for View-Invariant Gait Recognition, *IEEE Signal Processing Letters* 18 (7) (2011) 431–434.

[57] W. Kusakunniran, Q. Wu, J. Zhang, H. Li, A New View-Invariant Feature for Cross-View Gait Recognition, *IEEE Transaction on Information Forensic and Security* 8 (10) (2013) 1642–1653.