ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
Vol 5, Issue 4, April 2018

SECUR: Segment Based Evaluation of Co-factor Used in Human Gait Recognition

[1] Dr. P.S.Smitha, [2] Sruthi Nath C
[1] Asst. Professor III, [2] PG Scholar, Dept. of Computer Science and Engineering,
Velammal Engineering College, Anna University of Chennai, Chennai

Abstract: Gait recognition is an effective biometric feature to identify persons from a distance by the way people walk or run. Gait recognition technology is not limited to security applications; researchers also envision medical applications for the technology. For example, recognizing changes in walking patterns early on can help to highlight biomechanical abnormalities such as Parkinson's disease and multiple sclerosis in their earliest stages. The greatest turmoil in gait recognition is to identify an individual with cofactors and in sundry situations. View difference causes degradation of gait recognition accuracy, and so several solutions have been proposed to suppress this degradation. Thus gait identification of individuals with cofactors in multiple views becomes even more troublesome. In this paper we propose a method to descry cofactor affected probes in a stipulated range of views. Entire GEI Image is parted into three segments reckoning the occurrence of cofactor in it. The cofactor encompassed segment will be detected and eliminated. The segments are re-joined for final classification. The CASIA gait database is used here as a training and testing data. This is performed successfully for a given range of views with highly dynamic algorithms bringing forth a good accuracy rate and more adaptable than other prevalent methods.

Keywords: Biometric, Gait recognition, Gait Energy Image, security applications.

I. INTRODUCTION

There is an increasing research interest in human identification in controlled environments such as airports, banks, and car parks etc. as a security measure. Several biometric recognition systems are in hand for human identification such as fingerprint, face or iris recognition system etc. These are very efficient for accessing control applications where the subject's cooperation is expected, but is difficult to recognize humans at a distance. CCTV cameras are there in operation for this reason. Even though CCTV surveillance cameras provide enhanced security with wide acceptance, if the face of the person is obscure due to any changing environmental conditions or if the resolution of the camera doesn't support much, the technique won't shoot up as expected. The human GAIT is an important biometric feature for human identification in such video-surveillance-based applications. Gait recognition authenticates a walking or running person using the shape and motion information extracted from an image sequence of the person captured by a camera, and even the information extracted from relatively low resolution image sequences. Kinesiological parameters form the basis of gait recognition. The way you walk is more distinctive than you might realise. It may contain important clues to identify an individual. The most attractive feature of gait is its identification capability from a distance where as for other biometric systems; human identification is possible only with the close contact to the recording probe.

In addition to the noticeable security applications of gait recognition, researchers also envision medical applications for the technology. For example, recognizing changes in walking patterns early can help to identify conditions such as Parkinsonism disease and multiple sclerosis in their earliest stages. There are multiple military applications that include patrolling national borders, estimating the flow of refugees in troubled areas, monitoring peace treaties, and providing secure perimeters around bases and embassies.

Although gait recognition ensures promising characteristics and results, several challenges needs to be mitigated. One of the prominent challenges in gait recognition is to identify an individual with cofactors and in different emotional and environmental conditions such as walking speed, walking surface conditions, clothing, belongings, lighting changes etc. Also considerable degradation in the accuracy of gait recognition happens when there is a change in observation angles of camera used. Some of the other challenges are of physiological changes in the body of human due to aging, drunkenness, pregnancy, gaining or losing weight etc. In this paper we focuses mainly on the cofactor related issue in gait recognition. We also tried to consider the observation view problem and tried to mitigate the issue to a considerable level. Gait recognition usually consists of two main processes such as construction of gait energy image, GEI of a person for feature extraction and the next is the classification of gait pattern for recognition. Here the gait image is segmented into three segments and the segment that contains the cofactor is eliminated from the gait recognition procedure. The other two segments are combined and undergo the recognition procedure. The system is set in a way that even though the angle view is trained to be in 90 degree, the probe with angle view of 108 degree can be tested with considerable performance results.

II. LITERATURE SURVEY

1. View Transformation Model Incorporating Quality Measures for Cross-View Gait Recognition

The paper aims in lowering the degradation that occurs in view differences in gait recognition. A VTM (View Transformation Model) is proposed to supress the degradation where a gait trait with destination view is formed from that with a source view by estimating a vector on the trained joint subspace, and gait features with the same destination view are matched for identification. In accordance with the VTM incorporated framework, some quality measures that encodes the degree of bias is also added as normalization of biased scores improves recognition accuracy. VTM-based approach generally consists of three phases: 1) training; 2) transformation; and 3) matching. The training phase involves construction of the VTM using multi-view gait features of multiple training subjects. The transformation phase contains the generation of an input gait feature with a destination view from that with a source view. The matching phase involves the estimation for recognition. Two quality measures (Qt and Qb) are calculated to find the probability that multiple gait feature originate from the same sample.

2. Segment Based Co-factor Detection and Elimination for Effective Gait Recognition

The paper presents a method for detecting cofactor affected segments of GEI and an approach for dynamic reconstruction of cofactored GEI for more accurate recognition. The GEI image is split into three or four segments and the cofactor affected segment is analyzed. Thus the segment is avoided from the feature extraction and the rest is processed. The greatest advantage in this method is elimination of cofactored information from affected body segments rather than replacing them with earlier images. Even though this method performs good in cofactor affected segment identification, identification of gait image with cofactor information is performed only in a single angle of 90 degree.

III.PROPOSED SYSTEM

The system proposes a model for identifying person affected with cofactor and thereby increasing the performance as well as accuracy in human gait recognition. Cofactor affected segments of GEI (Gait Energy Image) is detected using segmentation technique and recognising the gait image of human more accurately. The whole GEI is first segmented into three parts considering the area of cofactor appearance in it. Cofactor information are detected and eliminated. Finally, the three segments are recombined for final classification. As an added quality the model also tries to confirm a person in another one view difference. This means a person with a source view can be matched with its any other destination view. Thus the system is tested for the view angles of 90^0 and 108^0 to confirm the angle variation identification.

IV. METHODOLOGY

The cofactored segments of GEI contain extra pixel values that are missing in GEI of the normal probe. These differences between the GEI of the normal probe and cofactored probe make the identification course degraded and hence the accuracy rate is dropped. As a counter measure, we developed a system to recognise cofactor accompanied probe by segmenting the GEI image and reconstructing the segment effectively by discarding the cofactor affected segment to crop out the extra pixel value problem. Generally there are two phases; training phase and testing phase that forms the whole system. In training phase, the GEI of the normal probe of certain view angle is trained and kept. Testing phase involves the recognition part where a cofactored probe with a different or same view angle is tested and matched with the trained images for identification. The block diagram of whole system with training and testing phase is shown in fig. 1.

A.Gait database

The proposed approach is tested on the CASIA gait dataset (Dataset B). Dataset B can be introduced as a large Multiview gait database which consists of 124 subjects. The gait data for these subjects will be captures from 11 views. Three kinds of variations, namely carrying condition, view angle and clothing changes are separately considered. The dataset B is highly suitable for testing the proposed system as it has a perfect blend of carrying condition and view angle variations.

ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)

Vol 5, Issue 4, April 2018

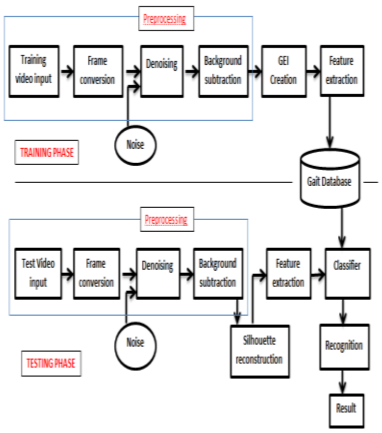

Fig.1. Architecture diagram for the proposed system considering the training phase and testing phase.

B. GEI Calculation

GEI is an average of silhouette images that has been obtained from the video input sequence. A single gait image is a collection of information of all the silhouette images. As many number of silhouettes we include that much information will be included in the gait. The GEI can be defined as

$$\text{GEI} = G(x, y) = \frac{1}{T}\sum_{t=1}^{T} A(x, y, t)$$

Where T is the number of frames $f_T = \{f_1, f_2, f_3, \ldots f_T\}$ of the video input. x and y are the pixel coordinates of the silhouette image, A. Frame number in the gait cycle is given by t. GEI of size 128x88 from CASIA database is used to evaluate the proposed method. GEI reflects major shape of silhouettes and their changes over the gait cycle.

C. Detection and elimination of co-factored segment

One of the challenging processes in the proposed system is the cofactor detection of GEI_{test}. The GEI from test input sequence are divided into three segments according to the predefined segment calculation of Avg_{GEI} which is an average GEI of around 20 segments. Dividing a GEI_{test} image is shown in fig. 2. Then the Euclidian distance is measured between i^{th} segment of *GEI test* and i^{th} segment of Avg_{GEI} . If the measured distance exceeds the predefined threshold value for the i^{th} segments, then it is considered as co-factored segment. Else the segment is considered as the normal segment. The same process is done for the other two segments also in the GEI_{test}. After the identification of cofactored segment the respected segment is ignored and the other two segments are merged for the further proceedings.

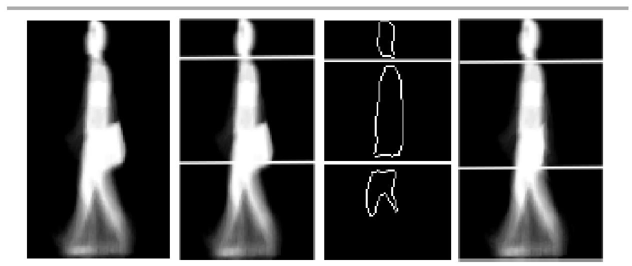

Fig.2. Segmenting a cofactored GEI $_{test}$ into three.

D. Feature extraction

Feature extraction of a GEI test image can be performed with numerous ways such as sigmoid feature, energy feature etc. The proposed model uses Histogram of Oriented Gradients (HOG) feature descriptor for the purpose. The technique counts occurrences of gradient orientation in localized portions of an image. This method is similar to that of scale-invariant feature transform descriptors, shape contexts and edge orientation histograms, but differs in that is it uses overlapping local contrast normalization for improved accuracy and is computed on a dense grid of uniformly spaced cells. Hog is shown to perform surprisingly well in human detection in still images as well as videos.

E.Confusion matrix

A confusion matrix is a table that is often used to **describe the performance of a classification model** (or "classifier") on a set of test data for which the true values are known. It is a special kind of contingency table, with two dimensions ("actual" and "predicted"), and identical sets of "classes" in both dimensions (each combination of dimension and class is a variable in the contingency table). Performance of such systems is commonly evaluated using the data in the matrix. The confusion matrix is mainly accompanied as an aid for the classification model. The classifier algorithm used is KNN classifier algorithm whose output is based on the nearest neighbour input. KNN algorithm works on three main steps that are

- Compute distance $D(x, x_i)$ to every training example x_i
- Select k closest instances $x_{i1} \ldots x_{ik}$ and their labels $y_{i1} \ldots y_{ik}$
- Output the class y* which is most frequent in $y_{i1} \ldots y_{ik}$

Where, x_i is an attribute-value representation of examples and y_i is the class label.

IFERP connecting engineers... developing research

ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
Vol 5, Issue 4, April 2018

V.COMPARISON

Feature selection on Gait Energy Image can be carried out with many processes such as sigmoid feature, energy feature etc. The proposed model is characterised with the Hog feature extraction process and it is compared with other two features namely sigmoid feature and energy feature. These features are the two divisions of Gait Information Image (GII) which is derived by applying the concept of information set on the frames in one gait cycle. They are generally termed as Gait information image with Energy feature (GII-EF) and Gait information image with Sigmoid feature (GII-SF). The comparison chart shows the performance of the hog feature extraction used in the proposed model with the other two feature extraction models. The comparison table and chart between the existing feature models and proposed model is given in Table I and Table II.

Feature descriptor	Total no of sequences	No of probe identified	Accuracy %
Energy feature	248	56	23
Sigmoid feature	248	4	2
HOG feature	248	166	67

TABLE I. Comparison table of different feature descriptors

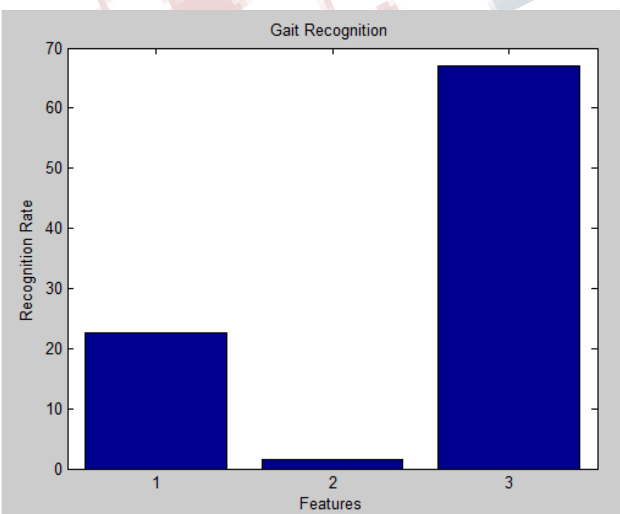

TABLE II. Comparison chart between the feature descriptors

VI. EXPERIMENTS AND RESULTS

The database used for the evaluation of the effectiveness of the proposed feature selection algorithms is CASIA database which is an indoor gait dataset that consists of around 124 subjects captured from 11 different views. The database consists of around 10 video sequence of an individual in which 6 are normal walking sequences (Set 1), 2 carrying-bag sequences (Set 2) and 2 wearing-coat sequences (Set 3). The total number of video sequences in the database comes up to 13640. The first 4 sequences of each individual in Set 1 are used as the training set and the rest as the test set including the rest sequences.

The main approach of this paper is to provide a process of cofactored *GEI* detection with an angle variation. The most effective evaluation of the gait energy image turns out in side view. The experiment is first conducted with specimens without any cofactor affected contents in a view angle of 90^0(side view) and then extended to cofactored test subjects. The results obtained after testing a video sequence of a subject without cofactor is shown in fig. 3a & b.

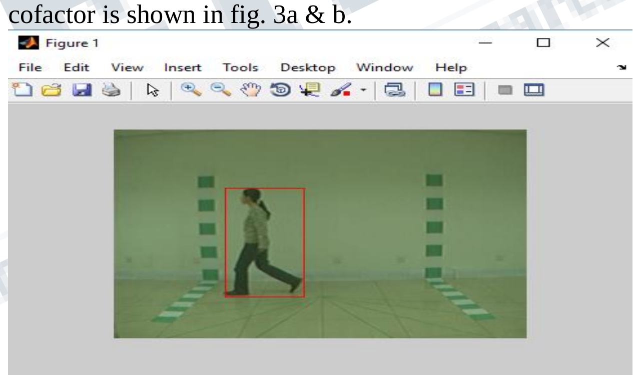

Fig. 3a. Evaluation of the video input of 16^{th} individual.

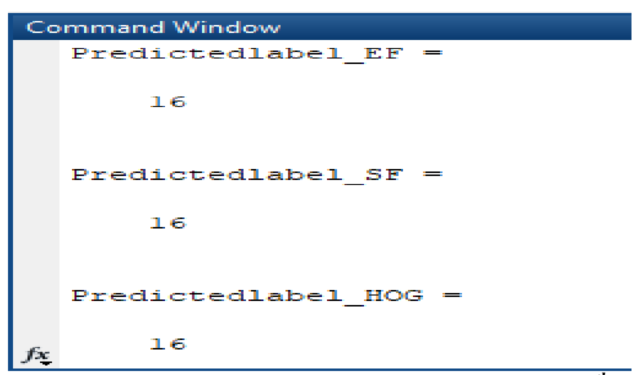

Fig. 3b. Output generated for the video input for 16^{th} individual without cofactor

ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
Vol 5, Issue 4, April 2018

The experiment is extended to identify a person with cofactor by dividing the test GEI into three segments by using some predefined values. The image is then identified whether it is a cofactor affected image or normal image by analysing the pixel contents in it. The cofactored segment is eliminated and the other two segments are taken for identification. The experimental results for an individual with cofactor are shown in fig. 4a & b.

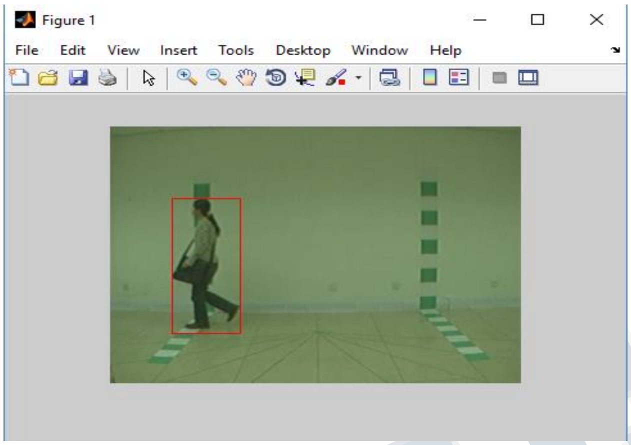

Fig. 4a. Evaluation of the video input of the proposed system for 16th individual with view angle 90^{0}

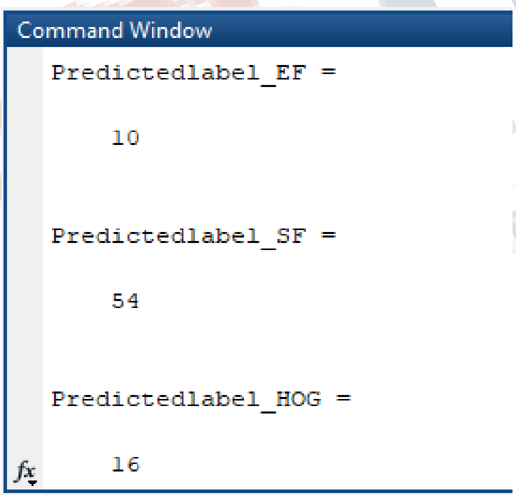

Fig. 4b. Output generated for the proposed model of 16th individual with view angle 90^{0}

The experimental results shows that compared to the other two existing methods, the proposed system could give an accurate result. The system is tested for the input video sequence set in a view angle of 90^{0}. The system is also tested for input video sequence with view angle 108^{0}. The results are shown in fig. 5a & b.

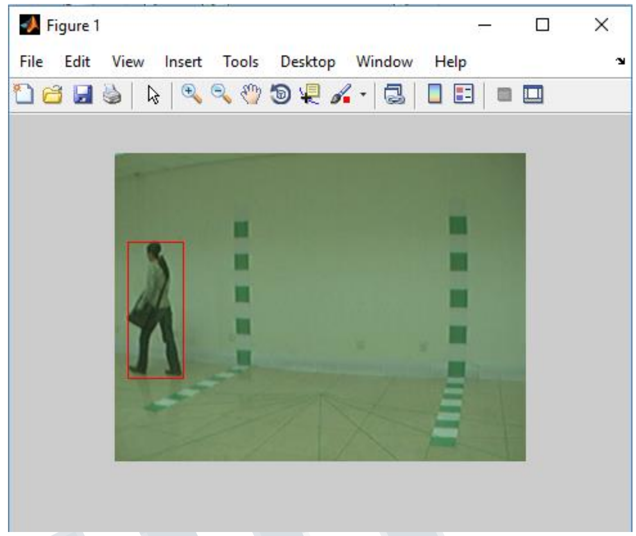

Fig. 5a. Evaluation of the video input of the proposed system for 16th individual with a view angle 108^{0}.

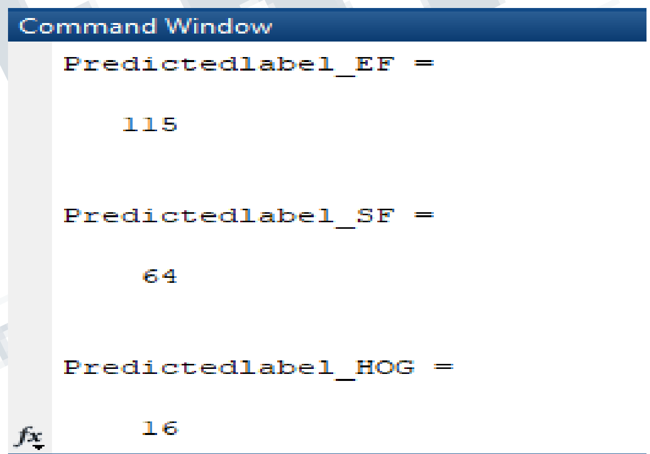

Fig. 5b. Output generated for the proposed model of 16th individual with view angle 108^{0}

VII. CONCLUSION

Human identification at a distance has gained more importance nowadays as there are increased security concerns. However, the appearance of different cofactors such as wearing clothes or carrying bags is one of the major barriers of this recognition system. The proposed system is designed to come across these barriers with a good accuracy rate. The systems involves in identification and elimination of the cofactor segment by segmenting a GEI image. The system is also capable to deal with a view angle variation to an extent. In future, the system can be extended by adding more cofactor contents such as

ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
Vol 5, Issue 4, April 2018

clothing styles, walking styles, environmental conditions etc. The method can also be demonstrated with different viewing angles applying on other datasets such as OU-ISIR, SOTON, Human ID and Treadmill Datasets for dynamic reconstruction of gait recognition. The proposed method shows significant performance while co-factors are present with any *GEI* image.

VIII. REFERENCES

[1]. Daigo Muramatsu, Yasushi Makihara, and Yasushi Yagi, *Member, IEEE,"* View Transformation Model Incorporating Quality Measures for Cross-View Gait Recognition*"* 2168-2267 _c 2015 IEEE

[2]. Abdul Matin, Jyoti Paul, Taufique Sayeed, "Segment Based Co-factor Detection and Elimination for Effective Gait Recognition,"2017 IEEE Conf.

[3]. Covariate Conscious Gait Biometrics Based on Zernike Moments Filtering - Thoughts on Computer Vision and Machine learning by Himanshu Aggarwal.

[4]. D. Tao, X. Li, S. J. Maybank, and X. Wu, "Human carrying status in visual surveillance," in *Proc. CVPR*, vol. 2. New York, NY, USA, Jun. 2010, pp. 1670–1677.

[5]. D. Tao, X. Li, X. Wu, and S. Maybank, "General tensor discriminant analysis and Gabor features for gait recognition," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 29, no. 10, pp. 1700–1715, Oct. 2011.

[6]. Effective part-based gait identification using frequency-domain gait entropy features - Multimedia Tools and Applications pp 3099–3120 (Springer).

[7]. Feature Extraction Methods for Human Gait Recognition – A Survey in Advances in Computing and Data Sciences pp 377-385 (Springer).

[8]. G. Shakhnarovich, L. Lee, and T. Darrell, "Integrated face and gait recognition from multiple views," in *Proc. CVPR*, vol. 1. Kauai, HI, USA, 2011, pp. 439–446.

[9]. J. Han and B. Bhanu, "Individual recognition using gait energy image," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 28, no. 2, pp. 316–322, Feb. 2006.

[10]. S. Sarkar *et al.*, "The human id gait challenge problem: Data sets, performance, and analysis," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 27, no. 2, pp. 162–177, Feb. 2013.

[11]. Sruti Das Choudhury, Tardi Tjahjadi," Silhouette-Based Gait Recognition Using Procrustes Shape Analysis and Elliptic Fourier Descriptors," IEEE Trans. Pattern *Anal. Mach. Intell*., vol:45, issue:9

[12]. W. Kusakunniran, Q. Wu, J. Zhang, and H. Li, "Gait recognition across various walking speeds using higher order shape configuration based on a differential composition model," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 42, no. 6, pp. 1654–1668, Dec. 2012.

[13]. Y. Iwashita, R. Baba, K. Ogawara, and R. Kurazume, "Person identification from spatio-temporal 3D gait," in *Proc. Int. Conf. Emerg. Security Technol.*, Canterbury, U.K., 2014, pp. 30–35

[14] R. Martín-Félez and T. Xiang, "Gait recognition by ranking," in *Computer Vision—ECCV* (LNCS 7572), A. Fitzgibbon, S. Lazebnik, P. Perona, Y. Sato, and C. Schmid, Eds. Berlin, Germany: Springer, 2012, pp. 328–341.

[15]. H. Iwama, M. Okumura, Y. Makihara, and Y. Yagi, "The OU-ISIR gait database comprising the large population dataset and performance evaluation of gait recognition," *IEEE Trans. Inf. Forensics Security*, vol. 7, no. 5, pp. 1511–1521, Oct. 2012.

[16]. A. Utsumi and N. Tetsutani, "Adaptation of appearance model for human tracking using geometrical pixel value distributions," in *Proc. 6th Asian Conf. Comput. Vis.*, vol. 2. Jeju, Korea, 2004, pp. 794–799.

[17]. P. Grother and E. Tabassi, "Performance of biometric quality measures," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 29, no. 4, pp. 531–543, Apr. 2007.

[18]. Khalid Bashir, Tao Xiang, and Shaogang Gong," feature selection on gait energy image for human identification", in ICASSP 2008 1-4244-1484-9/08, IEEE