Research Journal of Applied Sciences, Engineering and Technology 11(11): 1238-1244, 2015
DOI: 10.19026/rjaset.11.2231
ISSN: 2040-7459; e-ISSN: 2040-7467

Submitted: July 24, 2015 Accepted: September 14, 2015 Published: December 15, 2015

Research Article

Elliptical Model for Normal and Abnormal Gait Classification

[1]S.M.H. Sithi Shameem Fathima and [2]R.S.D. Wahida Banu
[1]Syed Ammal Engineering College, Ramanathapuram, India
[2]Government College of engineering, Salem, India

Abstract: The proliferation of innovative recognition and surveillance systems encompasses several algorithms and techniques. Human gait based recognition system, a subset of behaviour-based biometrics such as style, skills, language designs, support recognition and surveillance. In this manuscript, we propose to classify human gait as normal gait or abnormal gait through silhouette reconstruction and ellipse-fitting model. In ellipse-fitting, this article proposes a novel method of expanding the bounding box by covering human gait from head to toe for providing robust information about an individual as compared to the contemporary methodologies that acquire gait features from head to ankle. The other objective of this study is emphasizing the requirement of storing abnormal human gaits in databases for efficient recognition and surveillance, thereby improving the processing time coupled with the recognition rate. The Sparse Representation classifier (SRC) automatically classifies the normal and abnormal gait based on the characteristic vectors. The solicitation of 105 subjects facilitated the definition of the test sample. A camera with lower resolution recorded each subjects' images of normal and abnormal walking pattern. An extensive iterative process determined that the proposed method achieved 99.52 % classification accuracy, using SRC in contrast to the state of the art methodologies and basic classifiers.

Keywords: Ellipse-fitting, elliptical feature extraction, features vectors, gait classification, silhouette reconstruction, sparse representation classifier

INTRODUCTION

The incremental demand for surveillance systems necessitates an unobtrusive way of identifying a person. Human gait biometrics enables monitoring, without interfering in the individuals way of performing his activities. In video surveillance and computer vision field, segregation of multiple classes of individuals in various scenarios induce more complexity, as most of the existing classification methods do not account for the person's physical or behavioural features. Of late, human biometric plays a key role to identify a person, by associating his individual features obtained from face, iris, fingerprint, hand gesture etc. The emerging human gait biometric involves walking pattern of an individual. The gait recognition, a part of behavioral biometrics, employs human features such as gait cycle, stride length, stride width and knee angles. It serves as a supportive biometric considering various dress codes, speed variation, illumination changes that affect the recognition rate. In addition, the existing research leans towards rate of recognition for individuals with normal walking styles. A number of databases like CASIA, USF gait Challenge data set, CMU (MoBo) dataset, OU-ISIR database etc., have stored datasets of humans with normal walking pattern. Considering that, a substantial number of people have abnormal gait due to sudden or pre-existing medical conditions, this research focuses on the aspect to improve the recognition time and recognition rate. The human gait, when classified as normal or abnormal serves to route the processing accordingly. The main objective of this research is therefore classifying normal or abnormal gait pattern with sparse representation techniques. The methodology adopted had a test sample that consisted of normal or abnormal walking pattern. The part of abnormal gait pattern included Antalgic gait, Circumduction gait, Charlie-Chaplin gait, Steppage gait and Scissor gait. The purpose is to obtain the correct classification from the sample with automatic gait recognition. The Sparse representation has an active role in human recognition systems and improves the pattern classification. SRC directly uses the training samples of all classes as the dictionary to code the query; image and classifies the query image by evaluating which class leads to the minimal reconstruction error. The Sparse Representation based Classification (SRC) scheme shows interesting results in gait recognition problems; however, the SRC first codes a testing sample as a sparse linear combination of all the training samples and then classifies the testing sample by evaluating which class leads to the minimum representation error.

Corresponding Author: S.M.H. Sithi Shameem Fathima, Syed Ammal Engineering College, Ramanathapuram, India

The main contributions of this study include:

- Creation of dataset with normal and abnormal gait using 105 subjects comprising of both male and female with their ages in the range of 18 to 35.
- Fitting the ellipse horizontally on leg portion and vertically from head to toe portion to extract elliptical features such as length of major, minor axes (MA_1, mA_1, MA_2, mA_2) and orientation of the ellipses (Φ_1 & Φ_2).
- The features vectors or the digital storage of spatial data of a human silhouette from the test sample are then extracted using the lengths (MA_1, mA_1, MA_2, mA_2) and the orientation angles (Φ_1 & Φ_2) of vertical ellipse with respect to the centroid of the human body and the horizontal ellipse with respect to the centroid of the leg portion
- Clear and quality human silhouette results by applying a morphological filter on the features vectors. The features vectors function as an input to the Spare Representation Classifier (SRC) that classify the test sample as normal and abnormal.
- A new algorithm for accomplishing the surveillance systems efficiency and obtaining clear human silhouettes out of real-time, low-resolution images using the sequence of steps out lined above is termed as the pre processing algorithm used for matching and recognition.
- Experimentation of the proposed method with the created dataset coupled with various types of classifiers assists in selecting the efficient SRC classifier.
- This pre processing methodology realises the goal of achieving a high degree of accuracy in classification of persons with normal or abnormal gait.

The main objective of this research work is therefore, to study the effect of classification of human gaits as normal and abnormal types for reducing processing time and improvement in recognition rate of humans under surveillance. This study in addition evaluates the inclusion of the head to toe features of an individual to improve the classification accuracy by Sparse Representation Classifier (SRC). The other objectives are to highlight the importance of human gait based recognition systems and drawbacks in this promising field such as lack of attention to abnormal gaits.

LITERATURE REVIEW

A holistic view of gait based recognition involves a model based approach and model free approach. Model based approach uses the human physiology and standard static models. The models utilize the arm and leg movements and human posture. Moreover, the model based approach uses prior knowledge about a person. Cunado *et al*. (1995) modelled the leg as a pendulum. The gait signature extracted could withstand differing amounts of noise and occlusion. This method achieved recognition rates of 100% on a database of ten subjects. Cunado *et al*. (1999) considered only the leg portions to extract the gait signature and the legs were modelled as the motion of interlinked pendulum. The Hough transform technique extracted the lines that represent the legs in a video sequence. Recording of change in the inclination of these lines and Fourier transform analysis reveal the frequency change in the inclination of the legs. Zhang *et al*. (2007) proposed the static models say Hidden Markov Model was fit to the human body to measure and model the deviation. Niyogi and Adelson (1994) published the earliest research in computer vision based gait analysis techniques, based on spatio-temporal analysis and model fitting. Yan *et al*. (1994) published an algorithm based on a 10 sticks model and neural network classification. Little and Boyd (1995) published a gait analysis technique based on the spatial distribution of optical flow and the manner it varied over time. Model free approaches do not require any model, it directly work on image sequences (Lam *et al*., 2007; Liu and Wang, 2011; Huang and Boulgouris, 2008). In model free approach, gait energy image employment recognizes a person (Han and Bhanu, 2006; Lam *et al*., 2011). Flow energy image, frame difference energy images (FDEI) are used as various descriptors to identify the human. Nixon and Carter (2006) analysed the model-based approach with almost 114 subjects. They produced the recognition with various number of cluster values. Guo and Nixon (2009) proposed Improvement in classification accuracy obtained with elimination of redundant data and selection of optimal feature subset using mutual information. Amin and Hatzinakos (2012) proposed the usage of Empirical Model Decomposition algorithm that produced the recognition obtained with dynamic features from different parts of the body. Ng *et al*. (2009) evaluated the extraction of gait features with various angles with K-means Nearest Neighbour (KNN) classifier. They gave the authentication with wearing shoes, boots and walk with normal speed. Huang *et al*. (2010) proposed fusion of face and gait by image to class distance using a set of local features. Zhou and Bhanu (2007) proposed the Integration of face and gait for authentication is viable with enhanced side face images with the gait energy image. Begg *et al*. (2005) proposed a method for automated gait classification involving young and elderly subjects using Support Vector Machine (SVM) with improved classification and low error rate. Li *et al*. (2008) proposed the gender recognition using gait parameters. Here the silhouettes consist of seven components: head, arm, trunk, thigh, front leg, back leg and feet. Various approaches involve different algorithms. An effective algorithm to classify a person who has a normal or abnormal walk pattern is still scarce.

Rani (2014) proposed the classification of gait abnormality using Hybrid Extreme learning machine algorithm. Ranking procedure and T-Test produced top gait feature extraction. Training and testing with machine-learning algorithm performed the classification. HELM uses the Analytical Network Process (ANP) for choosing the input weights and hidden biases. Recognition depends on hidden layer weights of neural network. It produces 99.2% of real time data set classification using computing frame-by-frame abnormal gait classification made by optical flow patterns. This study has described a computationally efficient approach to abnormal walking gait analysis. Rohila *et al*. (2010) proposed a method that distinguished between normal and abnormal gait pattern. Appropriate person or personnel identify a suspicious person having abnormal gait. Seventy-five subjects walked on the track in real- time for the experiment. Real-world subjects with normal walk from the test sample for training the system. Aspect ratio, knee rotation, thigh rotation were taken into consideration for training and testing using nearest neighbour classifier.

Average minimum distance method in avoided the problem of selecting a random example as reference normal gait. That is, the mean distance to all reference manifolds belonging to normal walking gaits is calculated. The test considers as abnormal gait, if the distance is larger than a predefined threshold. Whenever the gait sequences are very similar then the results are good. When current gait seems deviated from previously stored or examined walking action then there is a challenge in recognizing that person. Liang (2006) proposed the motion metric histogram method to produce about 90% abnormal gait classification accuracy. Experimental results showed that the system provides accurate detection of normal walking and can distinguish abnormalities as subtle as limping or walking with a straight leg reliably. Machine learning techniques learn like intelligence and cover a wide range of processes that are complicated to classify accurately. A numerous researches are going on in gait analysis to determine any abnormality in gait. Smith (2007) achieved better recognition using motion estimation up to 93.22%. The previously mentioned papers produce appreciable recognition for small data sets. Hence, real time implementation for a large dataset to separate normal to abnormal gait classes is required for better recognition. This study proposes a new algorithm for this purpose.

PROPOSED WORK

Figure 1 depicts the proposed methodology for categorizing the walking style as normal or abnormal gait. The block diagram consists of training and testing phases. Initially, a camera with low resolution recorded the gait of the persons in the training phase. A simple background subtraction algorithm extracts the human silhouettes. In order to efficiently classify the gaits as normal and abnormal gait the ellipses are fitted vertically and horizontally to cover the head to toe portion and to the leg portion as shown in Fig. 2. The elliptical features such Major Axis (MA) and minor Axis (mA) lengths as well as the orientation (ϕ) of both the horizontal and vertical ellipses are computed to serve as feature vectors. These feature vectors differentiates the normal and abnormal gait. In testing phase, the query gait is classified using SRC classifier based on the elliptical features.

Background subtraction: In order to perform the gait classification from the real time video frames, the region of interest is segmented out the video sequences. One of the most common and easiest methods to perform the segmentation is image subtraction technique. The known background image is subtracted from the current frames which initially compare the

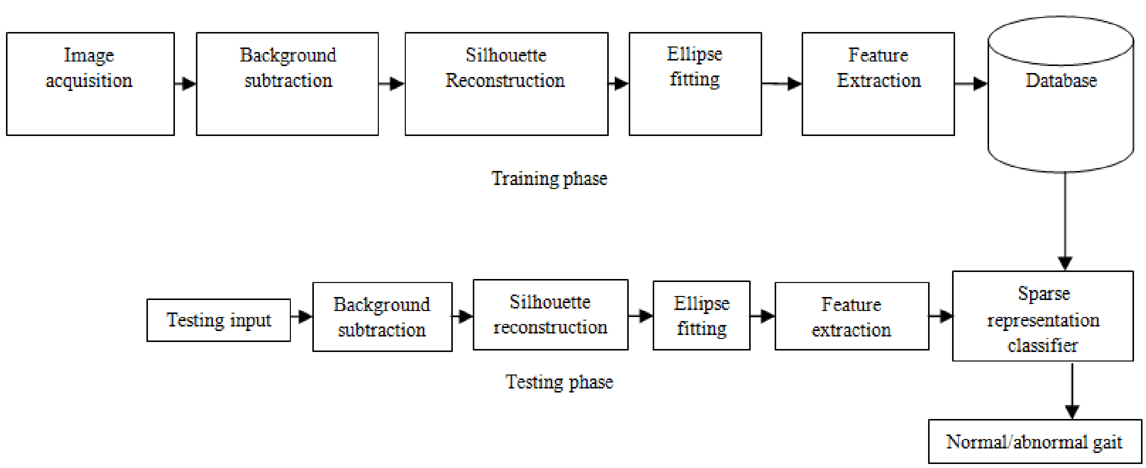

Fig. 1: Block diagram of the proposed ellipse fitting based gait classification

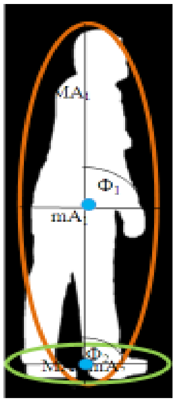

Fig. 2: Ellipse fitting model where MA_1, MA_2 denotes major axes, mA_1, mA_2 are minor axes and Φ_1, Φ_2 are the orientation of horizontal and vertical ellipses

intensities of connecting pixels, then threshold is applied to segment the region of interest. A pixel is considered as a part of the foreground when the current pixel value differs from its mean value by a pre defined threshold value is ϕ as shown in Eq. (1):

$$f(x,y)=\begin{cases} background & if \quad abs(I_{current}(x,y)-I_{known}(x,y))\leq\phi \\ foreground & otherwise \end{cases} \quad (1)$$

where,
$I_{current}$ = The current frame.
I_{known} = The background frame of the video and x, y are the spatial co-ordinates of the frame.

Feature extraction: The efficient elliptical feature extraction to distinguish the normal and abnormal gait is explained in this sub section. At first the vertical and horizontal ellipses are fitted on head to foot and leg portion respectively using least square method by Gander *et al*. (1994) as shown in Fig. 2.

Least square method uses the well-known Gauss-Newton method to fit the ellipse. Let $U=(U_1,U_2,U_{3,}...U_n)^T$ be a vector of unknowns and consider the nonlinear system of m equations:
Then

$$f(u)=0 \quad (2)$$

If m>n, then it can be minimized by the Eq. (3) in such a way that:

$$\sum_{i=1}^{m} f_i(u)^2 = \min \quad (3)$$

where, $u=(\psi_1,\psi_{2,...}\psi_n,\delta_1,\delta_2,\gamma)$ is the Jacobian associated with K and is denoted as j:

$$j=\begin{pmatrix} \gamma\eta & L \\ -\gamma\eta & M \end{pmatrix} \quad (4)$$

where $\eta = \text{diag}(\sin\Phi_I)$ and $N = \text{diag}(\cos\Phi_I)$ are mxm diagonal matrices. L and M are nx3 matrices where:

$$\omega i1 = -1, \omega i2 = 0, \omega i3 = -\cos\psi i$$

$$\alpha i1 = 0, \alpha i2 = -1, \alpha i3 = -\sin\psi i$$

For large n, j is very sparse. The first part of j $\begin{pmatrix} \gamma\eta \\ -\gamma n \end{pmatrix}$ is orthogonal.

In order to compute the kG decomposition of *J*, the ortho normal matrix k was taken:

$$k=\begin{pmatrix} \eta & C \\ -N & \eta \end{pmatrix} \quad (5)$$

If the centre is known initial approximation for $\{\psi_k\} where k = 1...n$ can be computed by:

$$\psi_k = \arg|(xk_1-\delta_1)+i(xk_2-\delta_2)| \quad (6)$$

Algebraic distance can be minimized by using quadratic equation:

$$y^T Ay + B^T X + C = 0 \quad (7)$$

With a symmetric and positive definite it can easily calculate the geometric quantities of the conic. Then the equation can be rewritten as:

$$\text{Let } A = \text{diag}(\lambda_{1,}\lambda_2) \quad (8)$$

$$\lambda_1 X^2 + \lambda_2 X^2 + C = 0 \quad (9)$$

It is determined that the least square problem can be solved by using this equation:

$$Y^T AY + B^T Y + C \approx 0 \quad (10)$$

And invariantly fit the ellipse with the condition expressed in Eq. (11):

$$\lambda_1^2 + \lambda_2^2 = \omega i1^2 + 2\omega i2^2 + \omega_{22}^2 = 1 \quad (11)$$

The parameter vector can be solved by:

$$u = (\omega_{i1}, \omega_{i2}, \omega_{22}, b1, b2, c)^T \quad (12)$$

With the constant $\|u\| = 1$ which is not invariant under Euclidean transformation

After fitting the ellipses, the measures such as length of the major and minor axis of vertical ($MA_{1,}$ mA_1) and horizontal ($MA_{2,}$ mA_2) ellipses are calculated. Further the orientation of both vertical (Φ_1) and horizontal (Φ_2) are computed to categorize the walking style as normal and abnormal gait.

Sparse Representative Classifier (SRC): The algorithm classifies the normal and abnormal gaits based on the extracted features as explained in the previous subsection using SRC Classifier. The SRC classifier is effectively performed well in noisy data. The SRC classifier categorizes the test data as described in following Eq. (13 to 16).

Consider a training set of $X = (X_1, \ X_2, \ X_3, \ X_N)$. Let X_j is the j^{th} class of training vector, N is the total number of classes. t_{ij} is the feature vector.

Let a test sample lies in class k. Then the equation can be written as in Eq. (13).

$$y = \lambda_{i1}t_{i1,} + \lambda_{i2}t_{i2} + ... + \lambda_{iN}t_{iN} \tag{13}$$

The Linear representation of Y is rewritten as $Y = Xu_0 \in JR^m$, where u_0 is a coefficient vector whose entries are zero except the j^{th} class. It is possible to obtain the class of Y using the above equation. In order to solve large classes l_1, l_2 norms are used to minimize and optimize the problem.

Given a sample y from one of the classes in the training set, initially compute the sparse representation $\hat{x}$, the non-zero entries in $\hat{x}$:
For:

$$l_1 norm \ \hat{x}_1 = \arg \ \min \|x\|_1 \tag{14}$$

Subject to $AX = Y$ geometric in $\hat{x}$, if the solution x_0 is sparse enough to the solution of the l_0 minimization problem and is equal to the solution to the following l_1 minimization problem.
For:

$$l_2 norm \ \hat{x}_2 = \arg \min \|x\|_2 \text{ subject to } AX = Y \tag{15}$$

And:

$$l_0 \text{ norm } \hat{x}_0 = \text{argmin } \|x\|_0 \tag{16}$$

EXPERIMENTATION

Dataset description: The abnormal and normal walking patterns of various persons were acquired by a static camera. The persons both female and male having 18 to 35 ages are considered to create the dataset. During video acquisition subjects wear different types of clothes, shoes and slippers. They were asked to walk on the track shown in Fig. 3a and 3b. Totally 105 subjects were considered for creating the dataset. The video has been recorded using SONY Handy cam HDR-CX240.It has CMOS sensor with size of 1/5.8 inch. Resolution of "1920 x 1080", "1440 x 1080", frame rate of 60 pixels. The distance between camera and track was around 25 feet and length of track was 20 feet. Three minutes of continuous walk converted around1200 frames in JPEG (. jpg) format with frame size of 1920 x1080 were obtained. These images were converted into silhouettes.

Fig. 3a: The normal gait cycle of a person

Fig. 3b: Abnormal gait cycle of a person

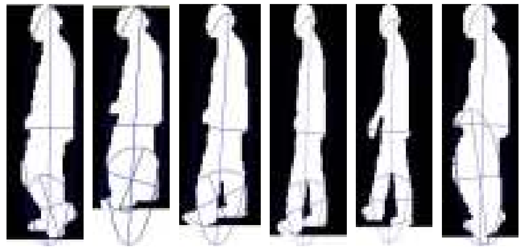

Fig. 4a: Ellipse fitting for Normal gait sequences for a cycle (OU-ISIR database)

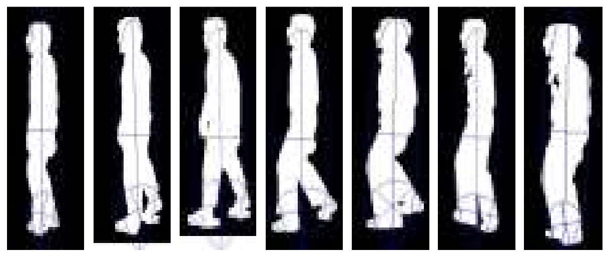

Fig. 4b: Ellipse fitting for abnormal gait sequences for a cycle

Figure 3a and 3b shows the gait sequences of a person with normal and abnormal walking style for a cycle.

Figure 4a and 4b show the ellipse fitted images of both abnormal and normal gait sequences.

RESULTS AND DISCUSSION

Table 1 shows the confusion matrix obtained by using KNN classifier. It produced 95.23% for normal to normal gait sequences (class 1 operation) with misclassification rate of 4.76% and abnormal to abnormal gait sequences produced 98.09% (class 2 operation) with misclassification rate of 1.90%.

Table 2 shows the confusion matrix obtained by using SRC classifier. It produced 99.04% for normal to normal gait sequences (class 1 operation) with misclassification rate of 0.95% and abnormal to abnormal gait sequences produced 100% (class 2 operation) with misclassification rate of 0%

Table 3 shows that the SRC classifier outperforms than KNN by the classification accuracy of 99.52%, Precision of 99.05%. The various performance measures are calculated using the given formula:

$$\text{Accuracy} = (\text{True Positive}+\text{True negative})/\text{Total} \tag{17}$$

$$\text{Misclassification} = 1\text{-Accuracy} \tag{18}$$

$$\text{Precision} = \text{True positive}/\text{predicted Yes} \tag{19}$$

$$\text{Specificity} = \text{True Negative}/\text{actual No} \tag{20}$$

The normal/abnormal gait classification using SRC classifier outperforms well in terms of classification accuracy, misclassification rate, Specificity and precision than KNN classifier.

Table 1: Confusion matrix obtained by K NN classifier

	Predicted class	
Actual class	Normal gait	Abnormal gait
Normal gait	95.24%	4.76%
Abnormal gait	1.91%	98.09%

Table 2: Confusion matrix obtained by sparse representation classifier

	Predicted class	
Actual class	Normal gait	Abnormal gait
Normal gait	99.05%	0.95%
Abnormal gait	0%	100%

Table 3: Comparison of KNN and SRC classifier for normal/abnormal gait classification

Performance measures	KNN	SRC
Accuracy	0.9666	0.9952
Misclassification rate	0.0333	0.0048
Specificity	0.9537	1.0000
Precision	0.9523	0.9904

Table 4: Comparison of state of the art method

S. No	Authors	Proposed Method	Abnormal gait classification accuracy
1	Liang (2006)	Motion metric histogram	90.00%
2	Smith (2007)	motion estimation	93.22%
3	Rani (2014)	Hybrid ELM	99.20%
4	Proposed method [2015]	Ellipse fitting	99.54%

Table 4 shows the state of the art techniques for abnormal gait classification accuracy. The proposed method produced the high accuracy than the earlier techniques.

CONCULSION

This research study presented a methodology for classifying the walking style as normal or abnormal gait. In order to distinguish the normal and abnormal walking style, this study adopted vertical and horizontal ellipse fitting algorithms on head to foot and leg portion of the silhouettes respectively. From the horizontal and vertical ellipses, the major and minor axis lengths as well as the orientations of both ellipses are calculated. The automatic classification has been done using SRC classifier based on the elliptical features. Furthermore the dataset of normal and abnormal gait is created using 105 subjects. The proposed methodology proved that it is efficient for categorizing the normal and abnormal gait to about 99.52% accuracy from the experimentation.

REFERENCES

Amin, T. and D. Hatzinakos, 2012. Determinants in human gait recognition. J. Inform. Secur., 3: 77-85.

Begg, R.K., M. Palaniswami and B. Owen, 2005. Support vector machines for automated gait classification. IEEE T. Bio-Med. Eng., 52(5): 828-838.

Cunado, D., J.M. Nash, M.S. Nixon and J.N. Carter, 1995. Gait extraction and description by evidence gathering. Proceeding of the International Conference on Audio and Video Based Biometric Person Authentication, pp: 43-48.

Cunado, D., M.S. Nixon and J.N. Carter, 1999. Automatic gait recognition via model based evidence gathering. Proceeding of the IEEE Workshop on Identification Advanced Technologies (AutoID '99), pp: 27-30.

Gander, W., G.H. Golub and R. Strebel, 1994. Fitting of circles and ellipses least squares solution. BIT, 34(4): 558-578.

Guo, B. and M. Nixon, 2009. Gait feature subset selection by mutual information. IEEE T. Syst. Man Cy. A, 39(1): 36-46.

Han, J. and B. Bhanu, 2006. Individual recognition using gait energy image. IEEE T. Pattern Anal., 28(2): 316-322.

Huang, X. and N.V. Boulgouris, 2008. Human gait recognition based on multi viewgait sequences. EURASIP J. Adv. Sig. Pr., pp: 1-9.

Huang, Y., D. Xu and T.J. Cham, 2010. Face and human gait recognition using image-to-class distance. IEEE T. Circ. Syst. Vid., 20(3): 431-438.

Lam, T.H.W., R.S.T. Lee and D. Zhang, 2007. Human gait recognition by the fusion of motion and static spatio-temporal templates. Pattern Recogn., 40(9): 2563-2573.

Lam, T.H.W., K.H. Cheung and J.N.K. Liu, 2011. Gait flow image: A silhouette-based gait representation for human identification. Pattern Recogn., 44(4): 973-98.

Liang, W., 2006. Abnormal walking gait analysis using silhouette-masked flow histograms. Proceeding of the 18th International Conference on Pattern Recognition (ICPR’06), pp: 473-476.

Little, J. and J. Boyd, 1995. Describing motion for recognition. Proceeding of International Symposium on Computer Vision, pp: 235-240.

Li, X., S.J. Maybank, S. Yan, D. Tao and D. Xu, 2008. Gait components and their application to gender recognition. IEEE T. Syst. Man Cy. C, 38(2): 145-155.

Liu, Y.Q. and X. Wang, 2011. Human gait recognition for multiple views. Proc. Eng.., 15: 1832-1836.

Ng, H., W.H. Tan, H.L. Tong, J. Abdulla and R. Komiya, 2009. Extraction and classification of human gait features. In: Badioze Zaman, H. *et al*. (Eds.), IVIC, 2009. LNCS 5857, Springer-Verlag, Berlin, Heidelberg, pp: 596-606.

Nixon, M.S. and J.N. Carter, 2006. Automatic recognition by gait. P. IEEE, 94(11): 2013-2024.

Niyogi, S.A. and E.H. Adelson, 1994. Analyzing and recognizing walking figures in XYT. Proceeding of IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pp: 469-474.

Rani, M.P., 2014. Abnormal gait classification using hybrid ELM. Proceeding of the IEEE 27th Canadian Conference on Electrical and Computer Engineering (CCECE, 2014), pp: 1-8.

Rohila, N., B. Kumar and N. Chauhan, 2010. Abnormal gait recognition. Int. J. Comput. Sci. Eng., 02(05): 1544-1551.

Smith, B.A., 2007. Determination of normal or abnormal gait using a two dimensional video camera, dissertation. M.S. Thesis, Blacksburg, Virginia.

Yan, G., X. Gang and T. Saburo, 1994. Tracking human body motion based on a stick figure model. J. Vis. Commun. Image R., 5(1): 1-9.

Zhang, R., C. Vogler and D. Metaxas, 2007. Human gait recognition at sagittal plane. Image Vision Comput., 25(3): 321-330.

Zhou, X. and B. Bhanu, 2007. Integrating face and gait for human recognition at a distance in video. IEEE T. Syst. Man Cyb., 37(5): 1119-1137.