

## 1 A Review on Human Gait Detection

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6 **Abstract**

7 The human gait is the identification of human locomotive based on limbs position or action.  
8 The tracking of human gait can help in various applications like normal and abnormal gait,  
9 fall detection, gender detection, age detection, biometrics and in some terrorist and criminal  
10 activity detection. The present work carried out is a review of various methodologies  
11 employed in human gait detection. The analysis describes that the different feature extraction  
12 and machine learning techniques to be adopted for the identification of human gait based on  
13 the purpose of the application.

14

15 **Index terms**— human gait, biometrics, machine learning techniques, feature extraction.16 **1 Introduction**

17 Human gait describes bipedal, biphasic forward propulsion of the center of gravity of the human body which  
18 involves the movement of various parts of the body without any additional energy requirement. The gait pattern  
19 can be categorized based on the different limb movement.

20 The presented work is a survey carried out on human gait. The general steps involved in the human gait  
21 detection are the background subtraction, silhouette extraction, feature extraction and classification of gait  
22 based on the objective of the respective work carried out. On the whole, the gait detection can be generalized  
23 and can be represented pictorially as shown in figure 1. The input to the gait recognition system is the video or  
24 the image captured from the camera. If video is the input, then it is subdivided into various frames and used  
25 as input to the gait recognition system. From the obtained image or video frame, the background is eliminated  
26 using some background subtraction methods. From that image, silhouette is extracted.

27 The silhouette extraction involves various methods like background subtraction, shadow removal, some  
28 morphological processes, etc. From the obtained silhouette the features are extracted. The extracted features  
29 are stride length, height, joint angle, etc. The complex feature extraction methods like PCA, LDA are used to  
30 extract prominent and essential features. The features selected play an important role in classification to make  
31 a decision of gait whether it is normal or abnormal.

32 **2 II.**33 **3 Related Work**

34 Kalyan Sasidhar and Satyam Satyajeet [1] proposed a wearable Smartphone based gait recognition system to  
35 detect normal and abnormal human walk. The limb movement is observed using the H accelerometer inserted  
36 in the Smartphone. The data is acquired using an application AndroSensor. The runs on the phone remove  
37 noise; extracts peak and valley points in the signal. The features such as stride length, step length, speed, and  
38 cadence were extracted. For classification threshold based classification of computed metrics based on decision  
39 tree classifier is used. The decision categorizes them into normal, mild, moderate and severe class based on the  
40 extent of the abnormality.

41 In this work, the Smartphone eliminates the need of visiting the clinic and hospitals. The persons can clearly  
42 diagnose by themselves. Cheaper compared to other expensive medication methods and easily reachable to  
43 ordinary people, especially women who are busy with multiple tasks. The drawback of this proposed work is

### 3 RELATED WORK

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44 the device must be worn around the ankle which is difficult, and the wearable sensors are not suitable for aged  
45 people due to their forgetfulness, and it's not appropriate for large scale deployment.

46 B. S. Daga, A. A. Ghatol and V.M. Thakare [2] proposed a process in which the main objective of the work  
47 is to detect the fall detection. The camera footage was considered for the curvature scale space (CSS) features  
48 extraction, and the human activity is classified based on the support vector machine (SVM) extreme learning  
49 machine (ELM) technique. In this work, the advantage of the ELM along with sparse representation coefficient  
50 (SRC) is also discussed.

51 The high accuracy obtained from SRC classification. Faster computation and response time of the ELM  
52 technique. The disadvantage is subjected to physical space constraint. The system will be used in monitoring  
53 subject falls and being alone in the house or room cannot get attention or raise the alarm for immediate help.

54 Hoang Le Uyen Thuc, Pham Van Tuan and Jenq-Neng Hwang [3] proposed a work in which ordinary camera  
55 is used to capture the video of a person moving such as doing actions or walking. The human object is  
56 segmented using a GMM-based background subtraction algorithm. The extracted human is then post-processed  
57 via morphology operations to create a well defined binary silhouette. Feature representation using two separate  
58 feature descriptors, one for each application scenario, and shape-based feature descriptor is good enough to  
59 represent the gait. Seven values of Hu's moments were used as features. The abnormal event detected based  
60 on Hidden Markov Model (HMM). The final stage is to convey an SMS message to the pre-defined cell phone  
61 number to notify the caregiver of a detected anomaly.

62 The installation, operation, and maintenance of the camera systems are simple. It is also non-intrusive,  
63 continuous, and objective in nature. But it is subjected to space constraints and can be an Automatic fall  
64 detection system to timely support the victims.

65 Zijuan Liu, Lin Wang, Wenyuan Liu and Binbin Li [4] proposed discrete wavelet transform (DWT) and  
66 principal component analysis (PCA) algorithms are used to remove noise. The two-dimensional CSI frames are  
67 built using the amplitude information of CSI subcarriers for extracting feature of CSI subcarriers. The SVM  
68 classifier is used to classify the CSI data. If there is a human movement, the gait periodicity is analyzed using  
69 autocorrelation to identify whether the intruder is human or not.

70 Since WiFi is available widely, this system can be adopted to detect the intruder easily.

71 Mohammed Hussein Ahmed and Azhin Tahir Sabir [5] proposed a gait-based gender classification method  
72 using the 3D skeleton data obtained from the Microsoft Kinect sensor. A Kinect sensor supported with SDK  
73 provides a human skeleton for two people. Kinect provides an RGB image and image depth. However, in the  
74 proposed method the author uses only a skeleton model. The proposed method consists of four stages. The first  
75 stage is the creation of an application by SDK for Windows to record a 3D skeleton, which is then used to create  
76 a database with Kinect. Detecting a gait cycle for each subject is the second stage. The third stage involves  
77 feature extraction -in this paper, the skeletonbased dynamic feature extraction method is adopted. In the final  
78 phase, the Nearest Neighbor (NN), Support Vector Machines (SVM) and Linear Discriminant Classifier (LDC)  
79 were used as the classification methods.

80 The human gender is easily classified without any human intervention. The information is collected through  
81 non-contact and non-invasive methods.

82 Ait O. Lishani, Larbi Boubchir and Emad Khalifa and Ahmed Bouridane [6] describe GEI which represents  
83 human walk using a single grayscale image obtained by averaging the silhouettes extracted over one gait cycle.  
84 The features of the GEI image is extracted using Gabor filter bank-based feature extraction method. To obtain  
85 useful and informative features for classification a Spectral Regression Kernel Discriminant Analysis (SRKDA)  
86 feature reduction algorithm is necessary. The SVM classifier is used to evaluate the categorization.

87 The recognition rate of the proposed method is high compared to other existing methods. Hence it can be a  
88 promising system in biometric applications.

89 Guan Y.D, Zhu R.F., Feng J. Y, Du, K., Zhang and X.R. [7] establishes the human silhouette and gait period.  
90 The author has adopted Shifting Energy Image (SEI) as the feature of the image, and then Gabor Wavelet  
91 and Local Binary Pattern (LBP) feature extraction methods are applied. Finally, gait feature will be classified  
92 and recognized by using sparse representation coefficients (SRC). The robustness of the system is high. Sneha  
93 Choudhary, Chandra Prakash and Rajesh Kumar [8] proposed a method consists of four steps. Gait Energy Image  
94 (GEI) is obtained by normalizing and averaging all the silhouette images in one gait cycle for all the subjects. The  
95 dimension of the GEI image is reduced by using principal component analysis. Five spatiotemporal parameters  
96 namely cadence, speed, height, stride length, stance period are calculated and concatenated with the reduced  
97 GEI Image. The reduced feature vector set is trained and tested using support vector machine and artificial  
98 neural network to classify whether it is male or female. The human recognition can be done from a far distance.

99 Nabeel Seedat, David Beder, Vered Aharonson and Steven Dubowsky [9] compare the force sensor based and  
100 accelerometer based motion monitoring system. The empirical mode decomposition (EMD) method is used to  
101 decompose, filter and reconstruct the respective kinematic signals. The threshold based peak detection is applied  
102 to estimate potential footfalls. The accelerometer sensor based system accuracy is good compared to the force  
103 sensor based system.

104 Wei-Yi Cheng, Florian Lipsmeier, Alf Scotland and Andrew Creagh [10] provide the continuous monitoring of  
105 the Parkinsons disease (PD) patients and motion monitoring. The sensor data for above 30000 hours were used.

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106 The convolution recurrent neural network was employed for human activity detection along with the extracted  
107 features.

108 The gait monitoring system is a promising system in the field of biometrics such as fingerprint, iris, DNA,  
109 and face. The consideration of gait for biometric would be advantageous compared to the existing one as the  
110 gait cannot be forged, and it is unique for each. Gait detection can play a significant role in the criminal and  
111 terrorist activities monitoring as they operate from a far distance. Since the gait detection doesn't involve any  
112 human contact, it can be analyzed from a considerable distance. Other than these the gait recognition would  
113 help in gender classification, age classification, fall detection and monitoring the aged people.

## 114 **4 III.**

## 115 **5 Gait Phases and Parameters**

116 The complete gait cycle has two phases: the stance phase and the swing phase. The stance phase consists the  
117 time when the foot is in contact with the floor and the swing phase when the foot is in the air. Each gait  
118 phase is associated with the sub-phases such as initial contact, loading response, mid stance, terminal stance,  
119 and pre-swing. The swing phases are an initial swing, mid swing, and terminal swing.

120 Initial contact (heel strike): It is the moment that the foot contacts the ground.

121 Loading response: This phase begins immediately after the initial contact of the foot and continues until the  
122 lift of limb for swing phase.

123 Mid-stance: Period starts from the lift of the contralateral limb from the ground to the point where the body  
124 weight is aligned with the forefoot.

125 Terminal stance: This period starts after heel rising in the frontal plane and continues to prior to the initial  
126 contact of the contralateral limb.

127 Pre-swing: This phase starts from initial contact of the contralateral limb and ends with the lift of the  
128 ipsilateral limb from the ground.

## 129 **6 Swing phase**

130 Initial swing: This phase, also called toe off, is from lifting the foot off the ground until the knee flexion is  
131 increased to its maximum position.

132 Mid-swing: This phase begins immediately after knee flexion and ends when the tibia is vertical.

133 Terminal swing: This phase begins following the vertical tibia position to just before the initial contact.

134 The Cadence: Total number of completed steps or number of strides per minute.

## 135 **7 Cycle frequency:**

136 The frequency obtained by performing the discrete Fourier transforms (DFT).

137 Gait cycle time: Time duration between two successive heel-strike events. Gait irregularity: The average SDs  
138 of the left and right step times. It shows the variability in successive steps of the same foot. Gait variability:  
139 The SD of gait parameters or their coefficient of variation (CV) i.e.  $CV = SD/mean$  which is based on stride to  
140 stride fluctuations.

141 Root mean square: Root Mean Square (RMS) of the acceleration magnitudes.

## 142 **8 Stance duration:**

143 The time from heel strike to toe off of the same foot. It is a percentage of the gait cycle.

144 Step asymmetry: The ratio of the difference between mean step times of individual legs to the combined mean  
145 step time of both feet.

146 Step duration: The time between heel contacts of the opposite foot.

147 Step frequency: Half of the fundamental frequency calculated using DFT.

148 Step length: Ratio of covered distance in meters to the number of completed steps. Step width: Distance  
149 between the heels in the double support phase.

## 150 **9 Stride duration:**

151 The time between two consecutive heel strikes of the same foot.

## 152 **10 Stride frequency: Number of cycles per second (Hz).**

153 Stride length: The distance between two consecutive heel strikes of the same foot.

154 Stride velocity: Ratio of the stride length to stride time.

## 155 **11 Swing duration:**

156 The time from toe-off to heel strike of the same foot that can also be expressed a percentage of gait cycle.

157 Walking distance: Multiplication of mean step length over a specified duration by the number of steps.

158 Walking intensity: Calculated from the integral of the modulus accelerometer output.

### 12 Walk ratio:

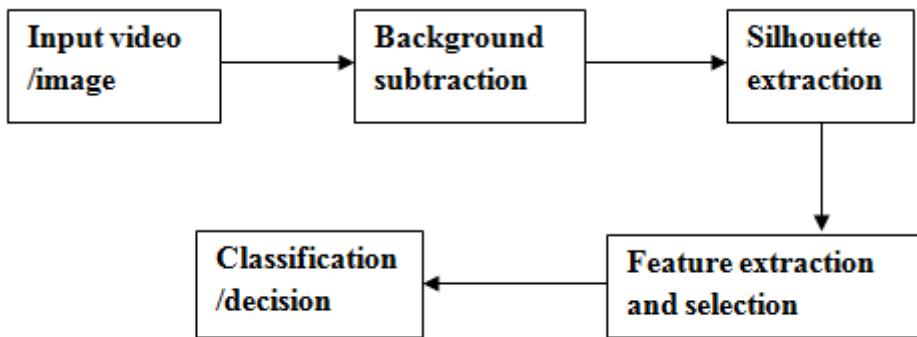
159 The ratio of average step length (in cm) to the cadence.  
160 Walking (gait) speed: Having distance divided by the walking time.  
161 Walking time: Measured using a stop watch.  
162 Walking velocity: Distance covered/number of data points/sampling frequency.  
163 Figure 2 shows the extracted silhouette from the original images after the morphological processes. The human  
164 gait cycle is a significant parameter in the gait analysis. Figure ?? represents how the gait cycle can be identified.  
165 IV.

### 167 13 Results and Discussion

168 The table1 shows the summary of the reviewed methodologies and their important parameters for gait analysis.  
169 The table2 shows the tabulation of the reviewed methodologies based on the applications. Other than this  
170 the human gait detection has applications in sport, computer games, physical rehabilitation, clinical assessment,  
171 surveillance, human recognition, modeling, and many other fields. V.

### 172 14 Conclusion

173 The work presented is a literature review work on human gait recognition. The silhouette extraction, feature  
174 extraction, and classification are the main steps involved in the gait recognition. The various methods were  
presented by the authors and all are reviewed in this work. <sup>1</sup>



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Figure 1: Figure 1 :



Figure 2:

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Figure 3: Figure 2 :



Figure 4: Figure 3 :A

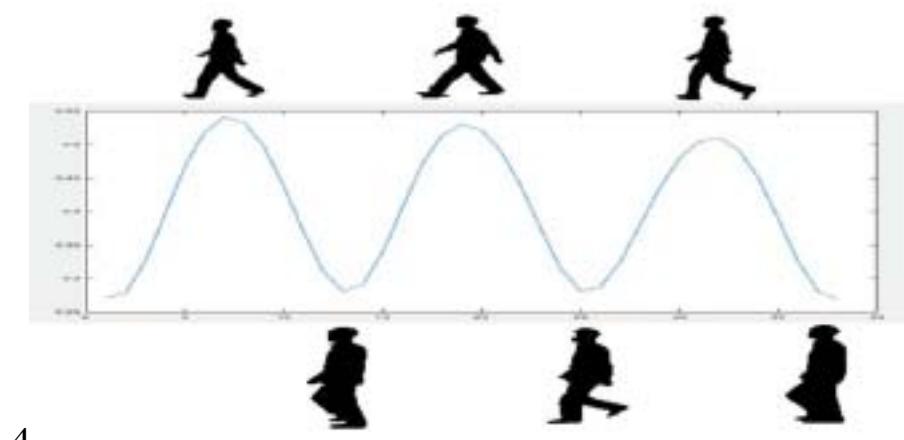


Figure 5: Figure 4 :

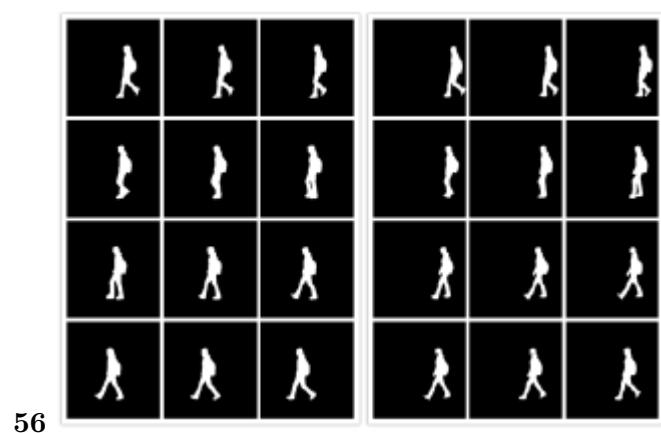


Figure 6: Figure 5 :Figure 6

Figure 7:

**2**

SI. No.	Application	Methods/Papers
1	Normal and Abnormal gait analysis	A Smartphone based personalized gait diagnosing system[1] [2],[3],[4],[9]
2	Fall and Position detection	[5],[8]
3	Gender detection	[5]
4	Terrorist or Criminal activity monitoring	[1],[10]
5	Medical applications	[6],[7]
6	Biometrics	

Figure 8: Table 2 :

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