Human Gait Analysis and Activity Recognition: A Review

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Abstract: **Gait refers the walking pattern of human being. It is the manifestation of change in the joint angles of lower extremity. Locomotion enables the person to perform the daily life activities, to maneuver over the discontinue surfaces. In this paper, we are presenting the systematic survey of bipedal legged locomotion and activity recognition. Human walking plays crucial role in our daily life activities. It provides the much needed mobility to perform daily life activities efficiently. Recognition of human activity is an intriguing issue that can be solved in a variety of ways. The majority of researchers recommended effective deep learning techniques such as CNN, inception CNN, LSTM, Bi-LSTM, and hybrid approaches. Human walk pattern reflects the health condition of any person. Various clinical examinations are performed through human walk to check their clinical success, post treatment recovery and rehabilitation. It also helps early diagnosis of various walking impairment at early stage. The main objective of this research is to review the different state of art gait analysis & activity recognition approaches for human health issues using various wearable sensors and other techniques. The discussion held in his paper would help the coming researchers in the field of human gait analysis and activity recognition.**

Keywords: gait analysis, wearable sensor, CNN, human activity recognition, deep learning, and bipedal locomotion.

I. Introduction

Biometric identification of human being can be done using physiological and behavioral traits. The gait is consider as a behavioral biometric [1]. It is a reflexive behavior which human being acquired through continuous learning. It evolves with age and decay with age [2]. The gait involves complex coordination of various body parts including brain, muscle etc. The impairment in any of above leads to disability and makes impossible to perform various activities such as walking, jogging, jumping, kicking, sit-down and, jumping etc.[3][4]. With the technology advancement various automated human activity recognition system have evolved [5] [6] [7]. These system helped in design of advanced health care monitoring system, smart home monitoring and many more Internet of Things (IoT) based intelligent system [8] [9][10]. These intelligent system containing sensors and actuators, the various system for HAR (Human Activity Recognition) are categorized into two parts sensors based and vision based [11][12] in Fig. 1.

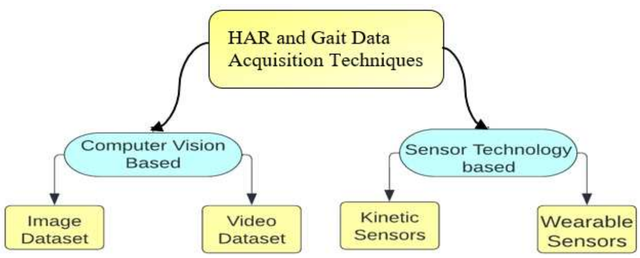
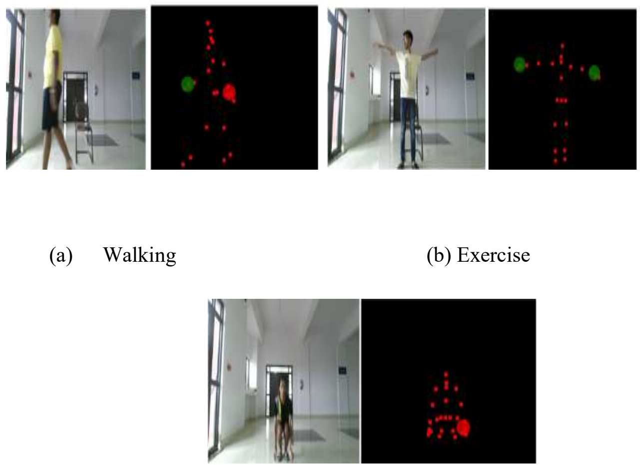


Fig. 1. Human Activity Recognition Approaches



(a) Walking (b) Exercise

(c) Sit-up

Fig. 2. Sample Image input of gait and HAR

In computer vision, cameras and video-based systems are also utilized to record routine human actions with automatic recognition carried out based on the image sequence. Currently, there has been a significant development in low-power, high-computing, and low-cost sensors as well as wired and wireless communication networks due to the improvement of microelectronics and computer systems [13] [14]. Fig. 2 shows the various input image of human activities and their skeleton joints image captured using Kinect sensors [15]. Although the video-based method frequently yields good results indoors, it is unable to achieve the same precision outside or in realistic conditions [16] [17]. Physiological characteristics can be controlled by wearable sensors, which make them easier to measure. Wearable sensors such as environmental or video sensors are attached [18] to the object being monitored and are not dependent on any external infrastructure.

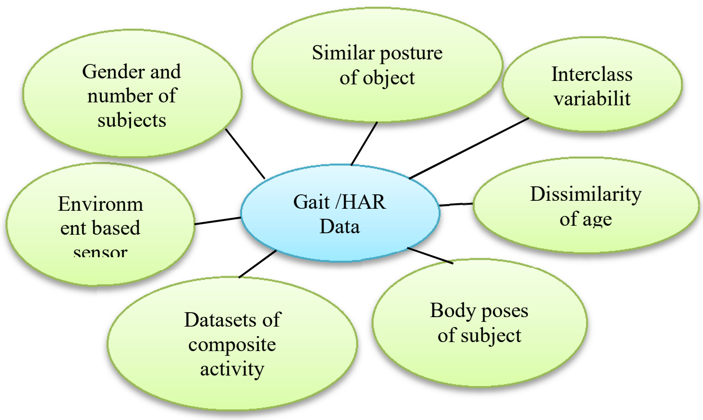


Fig. 3. Challenges in video-based and sensor-based HAR

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A. Challenges in human activity data set

A variety of sensors [19] are being used to capture the gait and HAR activities data. These sensors are popular in this domain and selecting the best sensors is difficult and challenging. This survey presents the various sensing technologies and papers published in the last decade. The three main categories of sensors are wearable sensors (such as accelerometers, gyroscopes, GPS, and light sensors) video sensors (such as cameras fixed in one place to detect activities), and environmental sensors for detecting user interaction with the environment (such as radio-based sensors like Wi-Fi and Bluetooth) [20] [21]. Additionally, we have an infrared sensor sometimes known as an infrared camera. Preparation of the dataset using video and sensor-based approach; the researchers have faced various challenges and difficulties which are depicted in Fig. 3. The challenges are listed here similarity between two posture, interclass variability issue, sequence of gait activities, sampling frequency of sensors, dissimilarity of age and many more [22][23].

B. Gait Biometric and terminology:

In this section, we discussed about gait meaning, related terminologies, background followed by the detailed discussion about different dataset, machine learning and deep leaning approaches used in the early times to nowadays. Human gait is the walking pattern of lower limbs generated by individual human being during locomotion. It is biphasic and bipedal in nature. The gait involves the coordination of left and right legs. During walking all the time one foot touches the ground. The gait can be measured using various spatiotemporal kinematic parameters, which may be classified into internal and external features. Table-1 presents the list of various spatiotemporal kinematic parameters.

TABLE-1: SPATIOTEMPORAL KINEMATIC PARAMETERS OF GAIT

Name of parameter	Category
Gait Cycle	Temporal
Stride Length	Spatial
Step Length	Spatial
Ground Clearance	Spatial
Cycle Duration	Temporal

Gait Cycle: Gait cycle is a repetitive pattern of the walking sequence of an individual. The time period between the heel strikes of one foot to the heel strike of the same foot is called as one gait cycle. It is also known a stride.
Stride length: Stride length is the distance between the same foot successive point contacts between initial and next contact.
Step length: Step length is the distance between one foot initial points of contact to other foot initial point of contact.
Cycle Time: The complete duration of the gait cycle and is the combined time of stance time and swing time.

C. Gait Cycle Phases:

There are two main phases swing and stance associated with each gait cycle, which further divided into 8 sub phases. Fig. 4 shows the percent wise division of gait cycle. The Percentage-wise division of gait cycle is as following:
Stance phase: In this phase foot remain in ground contact and 60% of gait cycle involves this phase. This phase is again divided into 5 sub phases.
1. Initial Contact– IC [0-2%] : Heel of the reference leg make the first contact with the floor.
2. **Loading Response– LR [2-10%]:** Loading response and the initial contact together constitutes10% of the gait cycle. It begins with the initial contact of the leg till the other foot is lifted for the swing.
3. Mid Stance– MS [10-30%]: This is the phase during mid-stance and this comprises of 20% of the gait cycle. This sub phase begins with the lifting of the other foot till the body weight is fore foot aligned.
4. Terminal Stance– TS [30-50%]: This sub phase comprises 20% of the gait cycle. The sub phase begins with the heel rise till the ground striking of the other foot. During the body weight moves ahead of the forefront.
5. Pre Swing– PS [50-60%]: This constitutes 10% of the gait cycle. The sub phase starts with the initial floor contact of the other leg.
Swing phase: In this phase, the foot and ground are not in contact of each other and it constitutes 40 % of the gait cycle. The swing phase can be further divided into three sub phases.
6. Initial Swing– IS [60-73%]: This sub phase accounts for 13% of the gait cycle. The beginning of this sub phase is with the lift of the leg above the floor till the swinging foot is opposite the stance foot.
7. Mid Swing – MS [73-87%] 14% of gait cycle is through this subphase.it starts when the swinging foot is opposite the stance leg and end s when the swinging limb is forward.
8. Terminal Swing – TS [87-100%]: This constitutes 13% of the gait cycle. In his sub phase leg is placed for initial foot contact to begin the next gait cycle. For describing the gait cycle one leg taken as reference and the movement of the reference leg are studied.

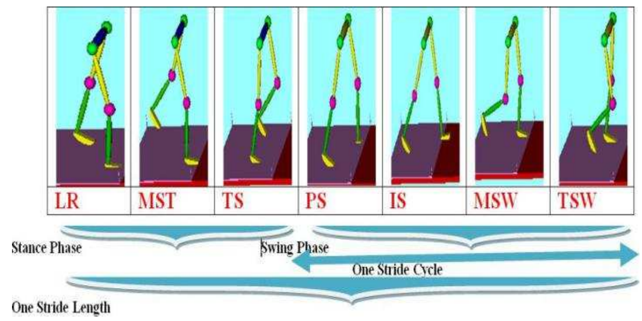

Fig. 4. Percent wise division of gait cycle

D. Challenges in Human Gait Recognition

As compared to other biometric techniques, gait recognition have its own set of unique challenges. The accuracy in recognition is most important in any biometric methodology. The gait recognition depends on many dynamics factors like disparity in viewing angles, type of clothes , footwear ,things an individual is carrying, speed of strides ,time elapsed, occlusions ,many physical deformities and ailments. The challenges faced gait recognition can be broadly categorized in to three types. Internal factors (pregnancy, aging, weight loss, limb disorder, etc.), External factors (things carrying by an individual, variations in clothing, view angles etc.), Occlusion type (static or dynamic) is the most occurring challenges. Occlusion primarily mainly occur when a group of two or most peoples walking together and the gait pattern of the individual concerned is concealed. The clothing pattern, Viewing angles and other challenged makes it more occluded to recognize the subject precisely. The feature in these scenarios become very important and decide the performance accuracy of the gait recognition system. Fig.5 depicts walking activity signal during one gait cycle and is suffer from interclass variability.

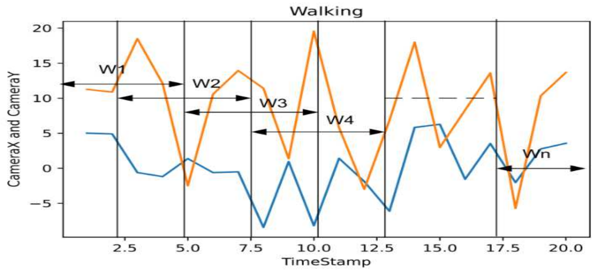

Fig. 5 Sample of walking activity triaxial accelerometer data

II. Steps Involved in Gait Recognition

There are five fundamental steps involved in gait recognition as gait data acquisition. Extraction of Silhouette from the background, Training and extraction of features from the Silhouettes, Selection of various features, Gait classification through the testing and training the feature space. Fig 6 shows the steps involved in gait recognition.

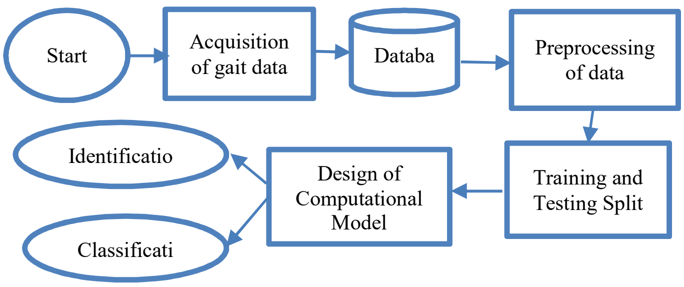

Fig. 6 Gait recognition steps

III.

Wang,X [24], proposed the method mentioned here upgrades the possibility of gait recognition from different view angles at different conditions. They merge several gait learner to propose a novel methodology which is an ensemble learning. They first splits half gait cycle to analyze differences of the human body work and used AAD model for gait feature extraction. Then they trained HMM learner to classify gait. A view based strategy is used to train HMM gait model. Furthermore they focused to deal with cross view gait recognition with the help of several state of art methods. The limitation is they confined their on 3 dataset for indoor scenes which becomes complex for outdoor scene. Also used conventional machine learning which does not combine with deep learning.

Christian Morbidoni [25] focused on trade mill walking data issues and proposed foot to floor contact for natural walking phenomenon and categorized swing and stance phases. Also suggested an approach to train the Deep Neural Network I.e. the sEMG signal. It focuses on natural human walking to increase the completion in gait phase classification and gait event prediction. Limitations are after minimizing the complexity of experimental protocol different noticing muscles should be valuable.

Gioegi [26] proposed methodology for data augmentation which focused on increasing classification accuracy level with make use of less number of sensors. A deep learning method based on Recurrent Convolutional Neural Network is used to find out gait analysis classification. The 3 axis acceleration classification sensor is used. Limitations Research work presented is identifying user in a plausible condition, where in built sensor s are smartphone and smart assets have been used.

Hazem [27] focused on transition between distances with curvatures of local contour. The Novel feature proposed here is more versatile than previous presentation of gait. They addresses to the new feature template issues. The new feature covers all detailed description of the subjects to increases recognition rates, used in their data sets to uplifts the performance .Also worked on multiple lower resolution version of one Dataset values. So it focuses on previous limitations of developed methods. The noticeable limit is nonlinear coupled learning which become challenging problem.

Torbene tepe [28] used Model based approach that combine skeleton poses with Graph Convolutional Network (GCN).Main focused on fine detailed extraction of the gait features and provided cooperation in Spatiotemporal modeling using GCN obtained result compared to the current model based approaches and also compared with appearance based methods. Experiments conducted on two dataset results in both model based gait recognition and competitive results found against in appearance based methods in gait recognition. Limitations Instead of mostly relying on the appearance spatial temporal mentioned here proves our claims to further back temporal gait features extraction.

Rahul [29] used autocorrelation method for stride segmentation of three different walking accelerometer data .It identifies stride boundaries, tuning parameter (tp), based on minimum standard deviation (for identification and extraction to specify stride data). It put efforts to eradicate the challenges associated with time series data and also clarifies the individual gait cycle in segmentation of signal samples into different stride specific information that used autocorrelation in declaration of stride boundaries. Different limitations occur during acceleration and ACF gait parameters estimations are also discussed.

Mgadalata [30] applied deep learning techniques on gait data

TABLE-2 COMPARATIVE STUDY OF METHODOLOGIES, DATASET AND ACCURACY

Research Paper	Methodology	Dataset used	Result Accuracy
Xiuhui wang et al.2020 [24]	1. CVGR-EL based on area average distance (AAD). 2. Reduces the sensitivity to variations of various view conditions.	CASIA OU-ISIR	92.7% which is 8% better than the existing state of art.
Christian Morbidoni et al. 2019 [25]	1. Electromayographic (sEMG) used to classify stance and swing phases for everyday walk. 2. ANN to classify gait events and to predict foot to floor contact signal from sEMG signals.	Laboratory of Universities Politeconica	Predictions may be considered reasonably suitable, since they show an average absolute error <1% and <2% of a gait cycle duration,
Giacomo Giorgi et al. 2018 [26]	1. Building and training of Recurrent Convolutional Neural Network based on gait reading through 5 body sensors. 2. Sensors filtering approach. 3. Study on cross session classification.	ZJU-Gait Acc 150 different identities	The accuracy is 99.06% with augmentation and 98.86% without augmentation. And an accuracy of 100% at rank 17 and 28.
Hazem EI et al. 2018 [27]	1. NDM that combines the distance transform with a curvature of local contour. 2. Evaluated the distance transform of binary Silhoutee then computed local HNV's on the counter levels of the distance map.	CASIA-B OU-ISIR OULP	The distance map. model has produced the accuracy 97%
Torben Teepe et al. 2021 [28]	1. Proposed GAIT Graph that combines Skeleton poses with Graph Convolutional Network to obtain a modern model based approach for Gait recognition.	CASIA-B	The CNN model has produced the accuracy of 98%
Jain et al. 2021 [29]	1. Autocorrelation procedure along with adaptive threshold using the tuning parameter.	HAPT OU-ISIR	Stride detection with accuracy rate of 94%.
M gadaleta et al. 2019 [30]	1. Deep learning model CNN is used to identify gait events.	Private Dataset	Inter-quartile range of 0.04s for foot contact.
Martindale et al.2021 [31]	1. Hybrid deep learning model combination of CNN and RNN layers.	FAU-Gait KLUGE MAREA	Determined error in mean stride duration is 5.5+/-51.9

of an older adults and in people with personal disability. Used algorithms on Wavelet transform (WT) focus on stride stance and swing phase. Validation process done over Parkinson's diseases and different severity motor system. They assessed it in the correct time localization of the initial and final foot content, stance and swing variability also mentioned in asymmetry negative bias situation. Limitations here noticed is the clinical personnel emphasis on therapeutic decisions and diseases progressions. The proposed extraction is suitable for unsupervised conditions.

Christine [31] proposed RNN architecture to recognize activities and cycles on data captured from IMU sensors. The Model is smaller than other comparable DL Models and also emerges robust in different sensors placements and channels. The large scale data expert's features absence noticed here. Time series length, CNN recognition rate, hyper parameter searches investigated here in detail. First Model to handle inertial sensor based Deep Learning.

IV. APPLICATION OF HUMAN GAIT ANALYSIS:

Gait is utilized in a wide range of modern day applications such as:

Gender Recognition: Identification of person gender (male and female) in a video while they walk. Earlier, researcher in their work [24] has presented the method which consider body, gait pattern and face. They performed the experiment with 6 people out of which three-man and three women with similar weights and heights. It is observed that speed of walking, swinging aims of the body do not affect the identification rate on identification of gender. The rotation of hip and hip shoulder movement also play important role in gender identification by walking pattern [24], [25].

Age Recognition: Speed of walking of a person, certain gait feature like step length, stride length of gait cycle of a person very much dependent on age of a person. Certain gait parameters like rotation of pelvic in different planes of movement's decreases as person get older. Bennett et al. in their work [32] has reduced hip flexion range, maximum hip extension, hip abduction and knee flexion extension. A minimum step length and reduced velocity in comparison with younger people group.

Medical Recognition Medical diagnostics : Orthopedics utilized Gait recognition for problems related to knee through gait patterns including stride speed ,stride length, etc., Parkinson's diseases identification based clinical applications. To detect various diseases, Gaussian neural network (GNN), principal component analysis (PCA) are used for better accuracy. Diseases like brain stroke and cerebral palsy are often takes advantages of gait recognition techniques as it helps in strategies for diagnosis and intervention for better management of the diseases. It is very useful in rehabilitations of such patient's .In sports for improving athletic performance and injury management often exploits the gait recognition. Gait recognition methodologies helps in gait disorders assessment and allow to understand the after effects of orthopedic surgery. Applications for osteopath etic and chiropractic: A pelvis or sacrum misalignment can also be diagnosis doctor and chiropractors may utilize various techniques to realign it and helps in restoring complete range of motion.

Biometric Gait identification Gait analysis is used to identify people through analysis of their unique walking pattern, because people repeat a specific pattern while they walk. So, it can identify people even if their face or other features are not visible. So without physical biometric also we can detect person by his gait analysis even if person is at far off place. So it is used in security and surveillance to identify suspicious person by their walking pattern.

Clinical Purposes: For clinical purposes, gait analysis is used to assess and treat individuals with conditions affecting their ability to walk.

Sports and Rehabilitation: It is used in sports bio mechanics to help athletes in injury rehabilitation by identifying their posture related or improvement related problems in athletes when injured. So that they can run efficiently.

Motion planning for humanoid robot: Gait abnormalities can be more precisely examined through the use of gait laboratories. These laboratories use kinematics evaluation of the lower limbs. Accordingly motion planning is done for humanoid robot to provide rehabilitation training to people.

Human Fatigue Analysis: It is used in human fatigue because due to tiredness persons walking pattern changes.

Various Performance parameters for measuring gait and HAR: Eq. 1-4 describes how the evaluation of results is depending on different performance measures. True Positive: The DL model accurately identified the true activity label for the test sample. True Negative: The test sample is successfully excluded from a specific label by the model. False Positive: An inaccurate label from the real sample is used to predict the test sample. False Negative: An inaccurate match between a predicted sample and its original label [33] [34].

$$Accuracy = \frac{True\_Positives + True\_Negatives}{True\_Positives + True\_Negatives + False\_Positives + False\_Negatives} \quad (1)$$

$$Precision = \frac{True\_Positives}{True\_Positives + False\_Positives} \quad (2)$$

$$Recall = \frac{True\_Positives}{True\_Positives + False\_Negatives} \quad (3)$$

$$F\_Score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (4)$$

V. CONCLUSION & FUTURE WORK:

This paper has presented the systemic study of HAR and gait analysis in last 5 years. Here, the details discussion of various data set, data set collection methods, model for gait recognition is presented. The paper has also provided the challenge and advance of current existing system for automated gait recognition and HAR. The current study can be used for design of model for gait and HAR recognition. The discussion held in his paper would help the coming researchers in the field of human gait analysis and activity recognition.

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