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Vision based Human Gait Recognition System: Observations, Pragmatic Conditions and Datasets

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Abstract

Background: Gait uniquely distinguishes the persons by using their physiological and psychological state. For this reason, human gait recognition at a distance recently gained wider interest from research community. In recent days, the concept of fusion based biometric systems has attracted many researchers and it is proved that gait can be valuable solution when all other biometric sources failed. However gait is still open research area. **Method:** The review explains the observations with the help of available data and scientific arguments of the experts in their documented works are also taken for our study. **Findings:** This paper provides a comprehensive survey of current developments on gait recognition approaches and emphasizes on three major phases involved in gait recognition system, namely representation, dimensionality reduction and classification. We also discuss in detail the pragmatic conditions of gait and efficient utilization of standard datasets in order to use gait recognition systems in masses. Also we highlighted the prominent guidelines to internal and external gait challenges. Further we provide the motivations for fusion of physiological and psychological biometric sources to accomplish practical scenarios. **Application/Improvement:** The study concludes that all previous attempts are restricted to only few external gait variations and evaluated on limited data set. However, there is no single attempt which addresses most of the external gait variations. Hence there is a scope for further exploration and evaluation.

Keywords: Authentication, Biometric, Fusion, Surveillance, Vision

1. Introduction

1.1 Biometric Systems

The field of biometrics research is still an emerging area, because of the demanding requirements for efficient automatic human authentication and authorization in security sensitive environments. Biometric resources such as iris, fingerprint, signature, speech and hand geometry, have been extensively studied by the researchers and are used in many applications. These biometric resources have their own merits and demerits; one of the major drawbacks is that, those fails in authentication of low resolution images. Another key demerit is that the user cooperation is required for good results. However, gait and face biometric resources do not suffer from the above mentioned drawbacks.

In forensics cases, if the perpetrator uses mask and gloves, no face and fingerprints can be captured. Also if the perpetrator projects his/her face in back view to the camera, in such cases face can't be captured properly. However, cameras can record the gait of the perpetrator absolutely. Further human gait can be obtained from images taken at a distance and it does not require user cooperation. Gait contains information about the walker's physical situation and about his/her psychological state. In certain cases gait information is sufficient to identify the person and it is very difficult to steal, fake or hide[4].

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1.2 Gait as a Biometric System: An Overview

In the technological perspective, biometric gait recognition can be grouped into three categories namely, Machine Vision (MV), floor sensor and wearable sensor based. According to the survey[4], many organizations prefer MV based recognition systems because of its simplicity, continuous authentication and also cost effective and non intrusive.

In this paper, we present a machine vision based gait recognition system. Gait is relatively latest, compared to the traditional approaches such as fingerprint, face etc. The below Figure 1 describes the general biometric authentication process.

Each person seems to have a distinctive and idiosyncratic way of walking, which can be easily understood from a biomechanics viewpoint. Human ambulation consists of synchronized integrated movements of hundreds of muscles and joints. Although these basic patterns of bipedal locomotion are similar for humans, gaits do vary from one person to another in certain details such as their relative timing and magnitudes.

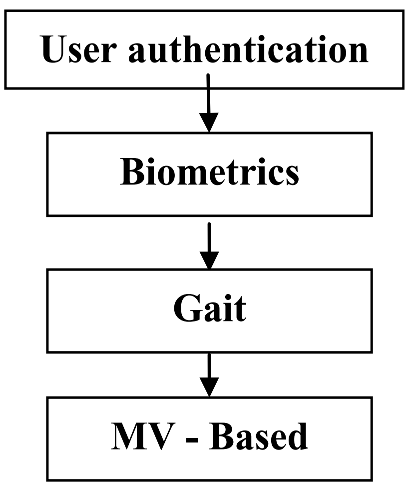

Figure 1. User authentication process.

1.3 Motivation for the Gait Research

Vision based human identification at a distance has recently gained wider interest from MV based research community. It is strongly driven by the need for automated person identification systems for visual surveillance and monitoring applications in security sensitive environments such as banks, parking lots, government secretariats, airports etc.

The combination of human motion analysis and biometrics in surveillance systems is an interesting research area in the present day. Multi modal biometric systems combine evidences from several biometric modalities to establish more reliable and accurate identification. In a multi-modal biometric system, gait helps in improving the accuracy of the system when it is integrated with other biometrics. Combining gait and face or iris, fingerprint etc may also be a good choice in realistic applications such as visual surveillance, access control etc. Hence, fusion of information provided by gait and other biometrics is an emerging and efficient in present biometric research.

An ongoing research project, the "Human ID program" initialized by DARPA (Defense Advanced Research Project Agency)[5], aims to develop a full range of multi-mode surveillance technologies for successfully detecting, classifying, and identifying humans to enhance the protection of facilities from terrorist attacks. Its focus is on dynamic face recognition and body dynamics including gait.

1.4 Applications

- Automated person identification systems for visual surveillance and monitoring applications in security–sensitive environments such as banks, parking lots, and airports etc.
- Gait recognition can also be used in forensics applications. For example[3], a bank robbery case in Denmark, a court found gait analysis as a valuable tool.
- Gait recognition technology is not only limited to security applications, it can also be used in medical diagnostics. For example basic changes in someone's walking pattern can be an early indicator of Parkinson's disease, multiple sclerosis and Normal Pressure Hydrocephalus (NPH)[47].
- Gait analysis is also used in professional sports training to optimize and improve athletic performance.
- Gait analysis can also use in gender recognition applications[48].
- Gait analysis can help us to find out the direction of the walking person.

1.5 External Challenges

The gait analysis is modulated or modified by many factors which are transient or permanent. Such prominent factors mostly impose challenges to the recognition approach. For example, views (e.g. frontal view, side–view), Backpack (e.g. Bag), object carrying (e.g. briefcase), speed (e.g. fast/slow/medium), surface conditions (e.g. hard/soft, dry/wet, grass/concrete/level/stairs etc.), shoe types (e.g. mountain boots), and so on[4].

Due to the importance of vision based human identification at a distance, a considerable numbers of research articles over the decade are listed below in evolutionary manner.

Huang[6] proposed an algorithm which employs Canonical Space Transformation (CST) for feature extraction and NN for classification. Six gait sequences used in training phase and the recognition rate for 36 test gait sequences is 100%. However, it addressed only view condition.

Hayfron et al.[7] described a symmetry map for gait representation and addressed only view conditions. Experiment were conducted on three small datasets namely, SOTON Small (16 sequences), UCSD (42 Sequences) and new SOTON (112 sequences) by using the symmetry operator, DFT and NN. The Correct Classification Rates (CCRs) is 100% for both k = 1 and 3 for the SOTON Small database. For the UCSD database, the recognition rates are 97.6% and 92.9% for k = 1 and 3, respectively. For the new SOTON database, the recognition rates are 97.3% and 96.4% for k = 1 and 3, respectively.

Wang et al.[8] apply the procreates shape analysis to silhouette shapes and extract a procreates mean shape from a sequence of silhouettes as gait signature. Then it is followed by PCA. It is a model free approach and experiment conducted on small NLPR Dataset. Method tested on 3 view condition in an outdoor environment. By using procreates distance measure, NN, K-NN and ENN as classifiers, encouraging EERs (Equal Error Rate) are about 8%, 12%, and 14% for side, frontal and oblique views respectively.

Work[9,25] proposed a model free approach which computes the distance between pixels along the contour and the shape centroid. Work[9] incorporated PCA where as[25] incorporated PCA+LDA as dimensionality reduction and discrimination analysis methods respectively. By using STC, NED as similarity measures and NN, KNN as classifiers, experiment demonstrates that algorithm of PCA and LDA are better than that of PCA.

Mark S. Nixon[10] implemented a silhouette windowing procedure to avoid variations due to distance from the camera. This technique uses the masking functions and signature is considered by computing the area of the silhouette within a mask. Then it is followed by canonical analysis. Masks are chosen to isolate a particular part of image. By using KNN, the CCR of 75% is achieved by combining information from different area masks. Experiment carried out on small SOTON dataset and addressed only view conditions.

In Murat Ekinci work[11], view distance vectors based approach is presented. The distance vectors are differences between the bounding box and silhouette, and extracted using four view directions. Thus, four 1-D signals are extracted for each view directions; they are top, bottom, left, and right views. Then it is followed by PCA. By using Mahalanobis and normalized Euclidean distances, recognition rates of 72% (Rank 1), and 100% (Rank 2) for a data set of 25 people, and 68% (Rank 1), and 100% (Rank 2) for a data set of 22 people are produced.

Dong Xu[12] proposed an algorithm based on a matrix representation. In this work, first binary silhouettes over one gait cycle are averaged. Then, Coupled Subspace Analysis (CSA) is employed as a preprocessing step and finally, a supervised algorithm namely discriminant analysis with tensor representation is applied to further improve classification ability. Experiments are carried out on the USF Human ID gait database which consist of 12 probe sets namely A,B,C,D,E,F,G,H,I,J,K,L and recognition rates (Rank-5) are 96,96,94,74,79,53,57,93,91,83,40 and 36 respectively.

Bo Ye[13] proposed an algorithm based on body contour. In this work, vectors obtained by horizontal, vertical and diagonal scanning of the outer contour of binaries silhouette of a walking person. A subspace transformation, which combines PCA with LDA, is applied to process the spatial templates. By using NN and KNN, algorithm performs an encouraging recognition rate of 87% on small NLPR dataset.

In Tao et al.[14] work, Gabor features based method is presented. The GaborD, GaborS and GaborSD representations are applied to the averaged gait images and general GTDA is employed to preserve discriminative information of Gabor features. Finally, LDA is used for classification. Method achieves around 74% recognition rate and experiment carried out on University of South Florida (USF) Human ID Database.

Toby[15] proposed a gait recognition algorithm that fuses the Motion Silhouette Contour Templates (MSCTs) and Static Silhouette Templates (SSTs). MSCTs and SSTs capture the motion and static characteristic of gait. By using NN, the algorithm achieved a recognition rate of around 85% on the SOTON data set and the recognition rate is around 80% in intrinsic difference group (probes A-C) of USF data set.

Boulgouris[16] proposed an algorithm which employs radon transform of binary silhouettes. For each gait sequence, the transformed silhouettes are used for the computation of a template. The set of all templates is subsequently subjected to linear discriminant analysis and subspace projection. In this manner, each gait sequence is described using a low-dimensional feature vector consisting of selected radon template coefficients. By using NN, recognition rates for USF's Gait Challenge database (probe sets A to G) are 100, 83, 76, 38, 36, 30 and 29% respectively for rank-1 and addressed only view and shoes conditions.

Martin[17] proposed two baseline algorithms namely color histograms; gait energy image to perform person identification in the presence of occlusion Further, PCA followed by Multiple Discriminant Analysis (MDA) is employed to achieve best data reparability. By using NN, two algorithms specifically address the occlusion problem and resulting in low recognition rates are 43.7 and 70.0% respectively. Experiment carried out on TUM–IITKGP which is the only dataset having occluded subjects available publicly.

Hong[18] proposed a mass vector based gait representation method which is defined as the number of pixels with a nonzero value in a given row of the binaries silhouette of a walking person. Then, Dynamic Time–Warping (DTW) approach for matching is used and the recognition rate is around 96.25% on small NLPR gait database is presented.

In Jianyi Liu[19] work, LDA is employed on Gait History Image (GHI) to achieve the best data reparability. Then, classification is achieved by the computing the minimum Euclid distance b/w the averaged GHIs from gallery and probe sets. Further, experiment carried out on CASIA dataset and achieved rank 1 recognition rate equals 90.1%.

Chen et al.[20] proposed the Frame Difference Energy Image (FDEI) based on GEI and GHI to address the problem of silhouette incompleteness. They calculate the positive portion of frame difference as positive values of the subtraction between the current frame and the previous frame. FDEI is model free approach which is defined as the summation of GEI and the positive portion. Further, Method tested viewing and synthesized occlusion (Horizontal and Vertical Bars) on limited CMU MoBo and CASIA gait databases. By using HMM, 80.03% 81.04% recognition rates for synthesized occlusion with horizontal and vertical bars respectively and 93.09% for viewing angles.

Guo and Nixon[21] presented three feature selection methods for gait recognition namely Mutual Information Analysis (MIA), which evaluates the statistical dependence between two random variables, feature selection by correlation Metric and Feature Selection by One-Way ANOVA. By using SVM, experiment carried out on Southampton HID Gait database and achieves 98.66% recognition rate for 55 Model based features, as well as 95.34% for 190 Model free features. In this work, MI based method outperformed the correlation–based and the ANOVA-based methods and experiments addressed only lateral view conditions.

Chen et al.[22] work uses two features namely frieze and wavelet features as gait information and extend HMM to construct a framework of Factorial Hidden Markov Model (FHMM) and Parallel HMM (PHMM). The FHMM and PHMM both have a multiple–layer structure. Experiments carried out on The CMU MoBo gait database and the CASIA - A and method addressed only viewing angles. Experimental results show that the FHMM tends to perform better than PHMM when only a few gait cycles are available for recognition.

Edward[23] proposed a human gait recognition system based on the simple extracted features over a bundle rectangle with the analysis of five classifiers such as height, width, area, diagonal's angle and total spectral power. The five measured features are compared by the recognition algorithm with each individual identification ranges stored in the database. The individual, who is present in all the feature matching lists, is considered as the recognized person. Simple extracted features over a bundle rectangle with the analysis of five classifiers are near to 98.6%.

Khalid Bashir[24] proposed a novel gait representation method termed as Gait Entropy Image (GEnI). In this work, algorithm constructs the GEnI then it is followed by CDA which is based on PCA and MDA. By using NN, recognition rates on SOTON, Human ID USF and CASIA are 89.37%, 70.63% and 53.5% respectively.

Sungjun Hong[26] proposed a width vector mean approach which is inspired by[18]. It is a Model free approach and experiments carried out on NLPR database. This work addressed only viewing angles. By using Nearest Neighbor (NN) approach, CCR is 90.0%.

Pushpa Rani[27] proposed an efficient self–similarity based gait recognition system for human identification using Modified Independent Component Analysis (MICA). The morphological skeleton operator is used to track the moving silhouettes of a walking figure. The MICA based on Eigen space transformation is then trained using the sequence of silhouette images. It is a model based approach. Experiments are carried out on small NLPR dataset. This work addressed only viewing conditions. By using NN, FRR of three views namely Lateral (L TO R), Oblique (L TO R) and Frontal (F TO B) are 1.2769, 1.6571, 2.0124, 1.8139, 1.0235 and 2.8766 respectively.

Liu[28] proposed a model free method based on outermost contour. Further, PCA followed by MDA is adopted here to achieve best class reparability. Nearest Neighbor (NN) classifier and Nearest Neighbor classifier with respect to class Exemplars (ENN) are used to classify the final feature vectors produced by MDA. Two other classifiers - Back Propagation Neural Network (BPNN) and SVM are also verified. Experimental results on a gait database of 100 people show that the accuracy of using MDA, BPNN and SVM can achieve 97.67%, 94.33% and 94.67%, respectively.

Pratibha Mishra[29] proposed a model based algorithm which is based on Bezier curves. Bezier curves are generated according to person's walk and recognition is achieved by matching those curves by calculating the mean and variance. Finally NN is used for classification. Experiment carried out on small CASIA–A and addressed only side views. The experiments results have obtained the CCR 100% for rank 5 and 85% for rank 1 on CASIA database, respectively.

Jyoti Bharti[30] presented a method which is based on graph of all pair shortest path distance. Firstly, algorithm selects the 4 points i.e. palm, knee, ankle and toe. All frames are connected to another frame using these four points and the graph is formed. Compute the Euclidean distance between the points or nodes. Calculated Euclidean distance is a weight between two nodes, by using these weights the all pair shortest path distance is calculated. Recognition is achieved by matching shortest path distance of input images with the database. Here, only the side-view of the person is considered. By using NN, The experiments results have obtained the recognition rate 95% for rank 5 and 75% for rank 1 on CASIA - A database, respectively.

Hayder Ali[31] work implemented the gait energy image, further which is followed by PCA with and without Radon Transform (RT). Experiment carried out on small CMU MoBo database and by using NN, Equal Error Rates (EER) of 94.23%, 82.28%, and 90.38% for PCA only and 96.15%, 82.70% and 92.30% for PCA with RT for slow walk, fast walk and carrying a ball walk respectively.

Mohan Kumar et al.[32] proposed an algorithm based on symbolic representation. Here, test samples represented by crisp feature values and training sample represented by interval-valued features. Experiments carried out on small CASIA-B dataset. This method addressed only views and carrying bags conditions. By using acceptance count, the overall average accuracy, precision and recall are 0.99%, 0.91%, 0.77% respectively.

Rohit Katiyar et al.[33] proposed a model free approach which uses Energy Deviation Image (EDI). Firstly, an original gait sequence is preprocessed and Enhanced Energy Deviation Image is obtained. Secondly, using Fuzzy PCA Eigen values and eigenvectors are formulated and which are finally termed as Fuzzy components. At last, NN classifier is utilized in feature classification. 45 Subject's gait used for training and recognition rate is 90.03% for 20 FPC is achieved.

Xiaoxiang Li[34] proposed Structural Gait Energy Image (SGEI), SGEI is generated by a fusion of Foot Energy Image (FEI) and Head Energy Image (HEI).Then it is followed by PCA. By using NN, Experiment carried out on CASIA (B) database and gets a recognition rate of 89.29%, which is much higher than GEI whose recognition rate is 60.37% only. This method addressed only views and carrying bags conditions.

Mohan Kumar[35] proposed two feature extraction methods namely three prominent temporal features, such as height, width and step length, secondly axis of least inertia. Experiments carried out on small CASIA-B dataset and average CCR is 88.65% .This Method addressed only views and carrying bags conditions.

Mohan Kumar[36] proposed a model free approach which is based on Change Energy Images (CEI). Further, CEI is followed by radon transform. Experiments carried out on small CASIA-B dataset and average CCR is 91.50%. This method addressed only views and carrying bag conditions. In work[35,36], test samples are represented by the crisp type feature values and training samples represented by the interval-valued features.

With the backdrop of above literatures, it is clear that a considerable amount of research has been carried out on gait recognition for individual identification. However most of them have addressed few challenges which are still far from practical applications. All previous attempts are restricted to only few external gait variations with less recognition rates and are evaluated on limited dataset. However, there is no single attempt which addresses most of the external gait variations. Hence there is a scope for further exploration and evaluation.

2. Observations

2.1 Observations Made on Gait Challenges

From the above, it is observed that some of the external factors have been addressed on limited dataset, further exploration and investigation on largest dataset is still open.

Some of the prominent internal factors which cause changes in natural gait that has to be investigated are due to sickness (e.g. foot injury, lower limb disorder, Parkinson disease etc.) or other physiological changes in body due to aging, drunkenness, pregnancy, gaining or losing weight and so on.

Moreover, to the best of our knowledge, so far internal factors of the gait have not studied in the context of biometric gait recognition. The reason behind that is more difficult to predict the health conditions and physical changes of a person. Internal variations has a direct effect on gait recognition performance However, Organization which needs gait based authentication system needs to cope with internal factors in order to develop robust gait recognition systems. As we know, it is more difficult to encounter these internal factors of gait so these can be easily overcome by applying some below mentioned prominent guidelines.

2.1.1 Ability to Update Training Set

However, it is easier to regularly update the database with revised biometric data as the user's characteristics change.

2.1.2 Using Multimodality to Enhance the Usability of Systems

Two (or more) modalities could be combined in parallel to produce a system that would allow more flexible use. For example biometric systems built for both gait and fingerprint recognition, could allow the use of only the fingerprint image for verification when users have problems enrolling their gaits and vice–versa. Moreover, this procedure could prove extremely useful to those users who have temporarily lost the ability to provide one of their biometric traits. A multimodal system therefore allows enhanced flexibility by providing alternatives for the identification process. As such, it also has the potential to be more socially inclusive.

2.2 Observations Made on Literature Survey

Although a considerable amount of research has been done, gait representation and recognition methods are still far from practical applications. A considerable number of papers describe the recent trends and developments on gait representation and recognition. Promising directions and list of observations made on literature survey are outlined as follows:

- A considerable number of works reported silhouette based methods because of its rich amount of desirable properties i.e. insensitive to the color and texture of cloth.
- With the backdrop of our survey, we found Model free and Model based gait representation methods. Most of the attempts in literature incorporated Model free approaches because of its characteristics. Model-free approaches focus on either shapes of silhouettes or the whole motion of human bodies, rather than modeling the whole human body or any parts of body. Model–free approaches are insensitive to the quality of silhouettes and have the advantage of low computational costs comparing to model–based approaches. Demerit of this approach is its relatively high space requirement.
- Few attempts clearly addressed Model based approaches[10,11,23,29]. Model-based approaches obtain a series of static or dynamic body parameters via modeling or tracking body components. Merit of this approach is its less space requirement. Model–based approaches are sensitive to the quality of gait sequences. Thus, gait image sequences of high quality are required to achieve a high accuracy. Another disadvantage of the model-based approach is its large computation and relatively high time costs due to parameters calculations.
- As indicated above, we found model based and model free approaches but only few attempts[15,35] have been employed on fusion. Combination of two approaches may be more effective than only using single approach. But these attempts tested on limited dataset and failed to

address prominent external variations of gait. So there is a scope for further progressive work.

- Most of the gait representation methods are restricted to either static or dynamic (motion) characteristics of human silhouette. Only few attempts[15,35] have been implemented on fusion. Combination of static and dynamic features may be more effective than only using either static or dynamic. But these attempts tested on limited dataset and reported less recognition rates so there is a scope for further work.
- In recent days, representing the real world objects using unconventional features (symbolic features) becomes an emerging technique in feature extraction area, With this backdrop, representing the gait using symbolic type features may be effective than using conventional data because gait varies with time within the same person. Moreover it captures both transitional and structural characteristics of gait. In Some cases, crisp valued type features cannot constitute gait information properly so that time symbolic type valued features may be the valuable tool. Clothing and walking speed conditions may easily solved by interval valued type features because of its rich set of desired properties i.e. range, more descriptive and well defined in nature.
- According to our survey on gait representation methods, there are many promising attempts which are based on conventional features have been implemented. But only few attempts[32,35,36] have been employed on symbolic approach. In these attempts, test samples represented by the crisp valued features. Sometimes, crisp valued type features cannot constitute gait information properly. These attempts employed on limited dataset, fail to recognize random sample, and addressed only viewing and clothing conditions. Hence there is a scope for further exploration on other external gait variations.
- Related works reported that only one attempt[17] has been employed on Occlusion. In work[17], Color histogram based method is explored but it faces many problems that color features fail in case of change in clothing, another drawback is that they are very sensitive to lighting differences especially when recognition is to be performed between differently calibrated cameras. Less recognition rates of 43.7%, 70% respectively are reported. Promising methods which will prominently solves occlusion problems yet to be proposed.
- Previous works reported that more attempts in literature demonstrated only on similarity measures but dissimilarity measures also have already proven their strength in many object recognition systems so promising dissimilarity measures yet to be proposed.
- A large number of papers in the literature reported good recognition results on a limited-size database, but only few of them made informed comparisons among different algorithms however extensive experiments and comparative analysis with recent methods needs to be demonstrating to examine the performance of the proposed algorithm.
- Promising combination of dimensionality reduction methods, discriminant analysis methods, feature transforms and feature selection techniques yet to be proposing in order to discard irrelevant and redundant information, as well as to identify the most important attributes. Few attempts in literature have already addressed this strategy but those attempts evaluated on small datasets, computationally expensive and addressed only few gait challenges. Hence there is scope for improvement.

2.3 Observations Made on Gait Datasets

With the backdrop of survey, Most of the researchers conducted their experiments on publicly available standard datasets namely CASIA (A, B and C), TUM–IITKGP and SOTON in order to test the performance of the algorithms.

The quality of a human silhouette has a direct effect on gait recognition performance. Hence researchers need to use morphological operations, such as erosion, dilation and closing etc to remove spurious pixels, fill small holes inside the silhouettes and to get fully connected complete silhouette. As indicated in previous paragraph, researchers widely used three standard databases, suppose if existed datasets not sufficient, they intend to create their own dataset by using background modeling and background subtraction procedures. Table 1 describes important features of the three publicly available standard datasets.

3. Pragmatic Conditions

With the backdrop our literature survey, In this paper, we identified eight major pragmatic conditions which are most often occur in human day life activities and are listed below.

- View modes are more important in gait recognition problem. Suppose we fix up cameras in controlled indoor environment, all cameras captures either side views or frontal views even person walks in any direction. Hence, we are focusing on side view and frontal view in order to accomplish random view condition. Biomechanics of human gait considerably vary in these two directions. Hence, views have a direct effect on the recognition results. To accomplish this objective, we measure some representative parameters such as step count, stride length, cadence, foot/hip angle, height/width of person, torso/leg length and amplitude of height oscillations etc in order to extract static and dynamic features.

- Backpack condition (i.e. bag) puts certain level of pressure on the normal gait nature. Hence this has a direct effect on recognition rates.
- Carrying conditions i.e. bags/briefcases/laptop disturbs the bipedal locomotion of a human due to their sheer weight and also alter the way the person appears especially in side views. Hence this has a direct effect on recognition rates.
- Different walking speed conditions i.e. regular walk, fast, and slow are most common gait variations. In a human psychology perspective, person walking speed may fast when he/she busy or having stress etc where as speed may slow when he/she in relaxing mode. Some essential parameters such as step length, step count, stride length, cadence and foot/hip angles relatively vary between regular walk and walk with fast/slow. Hence this has a direct effect on the recognition rates.
- Existence of occlusion i.e. static and dynamic. Static refers to occlusion by two standing people and dynamic refers to occlusion by two walking people. In occlusion problems, we get partial information of the subject where occlusion has occurred. Hence, we loose some essential gait information's. So, this has a direct effect on the recognition rates.
- Wearing conditions i.e. High heel shoe disturbs biomechanics of gait and changes the walking pattern of a person. Hence this has a direct effect on recognition rates.
- Some miscellaneous conditions i.e. hand in pocket, staircase climbing etc. Biomechanics of gait changes in these cases. Hence this has a direct effect on recognition rates.
- Outdoor pragmatic conditions i.e. hard and smooth surface.

Table 1. Important features of CASIA, TUM-IITKGP and SOTON gait databases

Name of Datasets Objectives	CASIA A	CASIA B	CASIA C	TUM-IITKGP	SOTON (Small and Large)	Total No. of Sub.
Only View mode	20	124	-----	35	115+12	306
Carrying Conditions	-----	124	153	-----	12	289
Backpack Conditions	-----	-----	-----	35	-----	35
Walking Speed conditions	-----	-----	153	-----	-----	153
Occlusion	-----	-----	-----	35	-----	35
Shoe	-----	-----	-----	-----	12	12

Table 2. Pragmatic conditions and Datasets

Database	No. of Subj.	No. of Seq.	Environment	Time	Variations
CASIA A	20	240	Outdoor	Dec 2001	3 View points
CASIA B	124	13640	Indoor	Jan 2005	11 Viewpoints, Clothing and Carrying Conditions
CASIA C	153	1530	Outdoor, night, thermal camera	Jul.-Aug. 2005	Speed (Normal, Slow and Fast) and Carrying Conditions
TUM-IITKGP	35	840	Indoor, Hallway, Occlusions	April 2010	Regular Walk, Hands in Pocket, Backpack ,Dynamic occlusion(Occlusion by two walking people) and Static occlusion (Occlusion by two standing people)
SOTON Small	12	194	Indoor	2001	View, Shoe, Carrying Conditions and Clothing
SOTON Large	115	2128	Indoor	2001	View

3.1 Pragmatic Conditions v/s Datasets

Most of the researchers conducted their experiments on publicly available standard datasets namely CASIA (A, B and C), TUM–IITKGP and SOTON (Small and Large). These datasets consist of considerably high number of subjects as well as address most of external gait variations. With the backdrop of our literature survey, some attempts have already made experiment on these datasets but they achieved less recognition rates, computationally expensive and failed to address prominent external gait variations. Hence still there is scope for further improvement and promising results. The Table 2 describes list of gait research objectives and utilization scheme of datasets.

4. Conclusion

This paper has presented a comprehensive review of the strategies in key stages and recent developments in gait recognition and identification. Three major issues of gait recognition including gait image representation, feature dimensionality reduction and gait classification are discussed. Features used to characterize gaits can be categorized into two major groups: model-based features and model-free features. Although a considerable amount of research has been developed, gait recognition for individual identification is still far from practical applications. All previous attempts are restricted to only few external gait variations and evaluated on limited dataset. However, there is no single attempt which addresses most of the external gait variations. Hence there is a scope for further exploration and evaluation.

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