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Human Gait Recognition: A Review

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Abstract--*The recognition of people by their physiological or behavioural characteristics is called biometrics. There are several biometrics that are being used for personal identification such as fingerprints, DNA, face, retinal scan, iris, voice, foot, hand geometry and gait.Gait analysis and recognition from digital video data has many applications. For example, digital video footage from subway stations, airports or other public places may be processed to find event exceptions in real time Similarly, studies have shown that humans have unique gait signatures which are not only different from the animals but they are also differentiable within the human race. It has been observed that the human motion contains strong periodicities while the animal motion does not show such characteristics. This property of gait can be used for object extraction and classification from digital videos for indexing and retrieval applications. Video data can be summarized and segmented using gait based descriptors for the intelligent browsing of the videos. Human gait analysis can be implemented to serve as identity verification for access control or criminology. This paper gives an in-depth analysis of various gait recognition techniques used forhuman classification.*

Keywords— *Biometrics, Gait, Feature vector.*

I. INTRODUCTION

Human recognition by gait was motivated by the psychological studies of the motion perception by Johansson [1]. Johansson used Moving Light Display (MLD) to study the motion perception. Light bulbs were attached to the person's joints in MLD experiments. Subjects were then filmed performing different types of motion activity such as dancing, walking and running in dark background. These films only show the collection of bright spots in a two dimensional plane and carry no structural information because the bright spots were not connected. The images of the bright spots were shown to different observers and it was noted that these scattered spots were meaningless to them. But when the films were played, the movement of the spots created impressions of a person walking, dancing and running etc. This shows that the relative movements of certain joints in the human body carry information about personal walking styles and dynamics. The position of light bulbs and corresponding point display is shown in Figure 1 for walking and running movement. It was also noted that the familiarity of an observer with a particular type of motion plays an important role in its recognition. The inverted MLDs were not recognized by observers as a walking or dancing pattern.

Figure 1. Contours of (a) Walking and (b) Running subject with point configuration.

C. D. Barclay et.al. Showed that the identity of a friend and the gender of a person can be determined from the movement of light spots only [2]. A database of 7 male and 7 female walkers was used in their experiments. They investigated the temporal and spatial factors in gender recognition by point light displays. They showed that the duration of dynamic stimulus plays critical role in the recognition. They determined a threshold of two step cycles for this duration. In the spatial domain, the shoulder movement for males and hip movement for females were found to be important determining factors. A very interesting observation was made when upside down film was played to the observers. It had the effect of reversing the gender appearance making females look like males and vice versa.

There are two main approaches to human gait analysis and recognition in marker-less systems. In the first approach, known as appearance based method, no *a priori* human geometric shape model is assumed. While in case of model based approaches, a priori geometric shape model is available.

II. MODEL BASED GAIT RECOGNITION

Model based approaches assume *a priori* human shape/geometric model to analyse the motion and shape of human body parts. There has been considerable work on tracking human body based on the shape models during the past few years. However, model based techniques with particular focus to gait analysis have not caught much attention of the researcher's community. This is partly due to the reason that tracking of human body is in itself a challenging problem involving very intensive computations. The geometrical model is usually parameterized and tracking of the shape is achieved by establishing the correspondence between model configurations and image features. The most common methods for tracking include Kalman filter [3], dynamic Baysian network [4] and condensation algorithm [5]. The model based approaches extract gait features from either static parameters or relative motion of joint angles. The static parameters such as torso height, leg length and stride are calculated from fitting the model in each frame and then further analysing it for feature extraction. The joint angle trajectories are calculated in some methods and gait features are extracted from them. The model based approaches can also be distinguished by the dimension of the shape model. The shape model can be 2D or planar or a 3D model. The following paragraphs include a brief description of model based works in human gait analysis and recognition.

Niyogi and Adelson formed an XYT spatio-temporal cube by stacking each of the frames in an image sequence one right after another [6]. A unique braided signature of walking patterns extracted by the XT-slice of the cube near the walker's ankle shows two legs criss-crossing over one another as the walker walks from left to the right. Their approach consist of finding translating blobs in image sequences, and testing if the XT slice of the lower half of the blob contains a gait signature. After detecting the human walker by this gait signature, the spatio-temporal edges for all XT-slices in the translating blob are recovered. A stick model of the person is generated from these contours which are then used for the gait recognition based on certain assumptions.

Gavrila and Davis recovered 3D body pose at different time instants from a sequence of images acquired from multiple views [7]. They used *a priori* knowledge about the kinematic and shape properties of the human body to make the tracking tractable. The purposed model has 22 Degrees of Freedom (DOF). They formulated the problem as a search problem of finding the pose parameters of a graphical human model whose synthesized appearance is the most similar to the actual appearance of the real human. Search space decomposition was used to overcome the problem of huge dimensionality (22D human). A novel similarity measure between the synthesized appearance and actual appearance is also defined which is based on the whole contours/regions rather than a few points. The ambiguity and occlusion problem in a one view is resolved by using multiple views. A database using 4 views with subjects performing different motion activities such as hand waving and Tango was used for experimental evaluation. The work was performed in context to deriving better gait features but they did not report any recognition results. Only the tracking performance of the technique was reported in the paper. Wren et. al. developed a real-time system called Pfinder to track and interpret human behaviour [8]. They used 2D model for tracking and detection of human body by Maximum a Posteriori (MAP) probability estimation. They modelled the human body as a collection of 2D blobs. These body blobs are described by spatial and colour Gaussian distribution. The foreground is segmented from the background by using a background model and blobs representing human hands, head and feet etc. are then fit over the foreground region. The body parts were identified by using a 2D contour shape analysis. The system was used for gesture control, recognition of American Sign Language, creation of avatars and to establish tele-presence.

Deutscher, Blake and Reid modified the particle filter for the tracking of articulated body motion with a large number of DOF [9]. They called their implementation of the particle filter as annealed particle filter. The complexity of the search problem increases exponentially with increasing number of DOF. In order to decrease the number of samples required to propagate over time for tracking, they used the concept of simulated annealing to modify the particle filter. The posterior conditional probability distribution of input state variable is represented by samples along with their weights. A simpler weighting function was used instead of directly evaluating the posterior probability for each configuration of the state variable. The motion of a model with 29 DOF was tracked with considerably less number of particles than the original condensation algorithm. The experimental evaluation showed a better performance than the condensation algorithm by using this strategy. In [10], Huang et.al. presented a method for human body tracking based on the 2D model. Their 2D card board model is the extension of the 2D scaled prismatic model with one additional DOF for the width change. They used a mixture model to represent the movement of the body. The motion parameters of the articulated body motion are solved using the Expectation Maximization (EM) algorithm.

Four static body parameters were used for gait recognition on a database consisting of 15-18 subjects by Bobick et.al. [11]. The extracted parameters were: vertical distance between the head and foot, distance between the head and pelvis, the distance between the foot and pelvis and the distance between the left foot and right foot. The distances were measured in number of pixels and a depth compensation mechanism was used to convert from image to world units. The gait feature vector is very compact but the recognition performance is low for rank 1. Yam et.al. Developed an automated technique capable of recognizing people from the walking as well as from running gait [12]. They used a modelling technique based on the concept of coupled oscillators and the underlying principles of human locomotion. The two approaches given in their paper derive a phase-weighted Fourier Descriptor (FD) gait signature by automated non-invasive means. Assuming the gait symmetry, the same model was used to describe either leg since both perform the same motion but out of phase with each other by half a period. These motions operate in space and time satisfying the rules of spatial symmetry and temporal symmetry. Both legs were modelled by two distinct coupled oscillators oscillating at the same frequency but with a phase difference. This model of forced coupled oscillators is fitted to the image data extracting the lower leg motion in both walking and running gait. The gait features were derived from the magnitude and phase of FDs of thigh and lower leg rotation. A statistical analysis was also performed to find the most effective feature set.

Green and Guan defined the alphabet of human movement called dynemes which are the smallest units of motion [13,14]. The combination of these units in different order forms different skills and activity. They developed a 3D clone body model which is dynamically sized and texture mapped to each person enabling both edge and region tracking. A particle filter with forward smoothing is used for the estimation of the parameters of the body model which has 32 DOF. The gait signature was extracted by using the Fourier series to describe the leg motion. The method was tested on a database of 58 people walking in a sagittal plane wearing tight fitting clothes. The training set consisted of 48 people while the additional 10 people were used for the testing. They achieved an accuracy of 88% by using the extracted gait signatures. The anthropometric features were also tested to evaluate their performance in human recognition. Interestingly, a recognition rate of 92% was achieved which is 4% higher than the gait based analysis. A combination of both gait and anthropometric features increased the accuracy to 94%. The method proposed by Raquel Urtasun and Pascal Fua is based on the fitting of 3D temporal motion models to synchronized video [15]. They not only achieved tracking by this method but also recovered motion parameters which were then used for human recognition. They formulated tracking problem as a minimization of differentiable objective functions whose state variables are the Principal Component Analysis (PCA) weights. The differential structure of these objective functions takes the advantage of standard deterministic optimization methods whose computational requirements are much smaller than those of probabilistic ones.

In [16], a 3D articulated body model defined by 16 links and 22 DOF was used with certain constraints on the movements of arms and legs to reduce the complexity. The motion trajectory of the walker's footprints is detected from the segmented video sequence. 3D human model is then moved on this trajectory driven by the prior motion model and the joint angles are adjusted to the walking style. The extracted joint angles were not used for recognition and only gait analysis was performed. A statistical model for detection and tracking of human silhouette and the corresponding 3D skeletal structure in gait sequences was proposed by Carlos et.al. [17]. A different point distribution model was applied depending on pose. The performance of the model is improved by taking into account temporal dynamics to track the human body. The incorporation of temporal constraints on the model helps increase the reliability and robustness. The 3D skeletal structure is extracted and tracked over time in the image sequence. Wagg and Nixon developed a new model-based method based on the biomechanical analysis of walking people and used it for recognition [18]. The image sequences were segmented to extract the moving regions and an articulated model is fitted to the edge by a hierarchical procedure. Motion estimation is performed by using a sinusoidal model for the leg and angle trajectories are extracted. The method is evaluated by using SOTON database and the feature vector is 63 dimensional. A recognition rate of 84% on the indoor dataset and 64% for the outdoor dataset was achieved.

Lu et.al. proposed a layered deformable 2D body model for gait recognition [19]. Their model is a full body model consisting of 10 body segments specified by 22 parameters. These 22 parameters define the size, position and orientation of the body segments. The limb orientation and position was estimated using mean shift algorithm for manually labelled silhouettes. The joint angles were then calculated from limb orientations and positions using simple geometry. A coarse to fine estimation based on the ideal human body proportions (eight-head height) was proposed for automatically extracted silhouettes. DTW was used for pattern matching between gallery and probe sequences. The performance of the features for gait recognition was not very impressive and it further degraded when automatic silhouettes were used. The average rank 1 performance of 25% was achieved for manually extracted silhouettes which dropped to 18% for the automatically calculated silhouettes. A 3D human body model consisting of 11 body segments was developed by Gu et.al. [20], the head was represented by a sphere and other segments were cylindrical. The model contains 10 joints with 24 DOF. The kinematic structure of the model was estimated by employing anthropometric constraints between ratios of limb lengths. After the body segmentation, adaptive particle filter was used to track the body segments. Gait features were extracted from pose parameters and joint position sequences. Two gait models were obtained from normalized joint sequence of the whole body and the normalized joint sequence of two legs using an exemplar-based Hidden Markov Model (HMM). MAP estimation was used for pattern classification. The test database consisted of multiple video streams of 12 subjects that were simultaneously captured from multiple static calibrated cameras. Volumetric representation sequences were created using visual hull method after foreground extraction. An average recognition rate of 94.4% was reported on the test database.

In [21], Arai et. al. reported gait recognition results on Chinese Academy of Sciences (CASIA) data set consisting of 31 male and 31 female subjects. They extracted silhouettes by simple background subtraction. The skeleton was then extracted using thinning and other morphological operations. Eight important feature points were then determined on the extracted skeleton structure. The skeleton was reconstructed by connecting 8 points with straight lines. Motion was also estimated using simple frame subtraction method. Discrete wavelet transform was used on skeleton data and motion signals to extract features for recognition. They achieved an average correct recognition rate of 95.97% on the test database.

III. APPEARANCE BASED GAIT RECOGNITION

The appearance based gait recognition methods first perform motion detection to segment the regions corresponding to the moving humans. Some form of shape analysis is then applied to these human image sequences to extract the gait signatures. Static body parameters such as lengths and widths of limbs, height of the person are extracted in some techniques and used to represent gait. Some works rely on the dynamic features that are extracted by shape changes and motion flow. Majority of the techniques in appearance based category work on human silhouette sequences.

In [22], Liu and Picard, presented an algorithm for simultaneous detection, segmentation, and characterization of spatiotemporal periodicity. The algorithm may be applied to find the periodicity in the images which can be used for the object detection and classification. The work is motivated by the notion that the human gait/motion is periodic. This characteristic has been used to separate and segment different objects from the images such as dogs and cars were separated from the human objects. The proposed algorithm acts as a *periodicity filter* and is computationally simple. It was shown to be more robust than optical flow based techniques in the presence of noise.

Meyer et.al. Modelled several body parts such as head, trunk and leg as well as the background as mixture densities in grey scale images [23]. They localized the body parts in every frame by mixture densities and accounting the anatomic relationships between the body parts. The mixture model is calculated using EM algorithm. Features are extracted from the trajectories and HMMs are trained. One HMM represents each kind of gait such as walking, running and dancing. Cutler and Davis developed a system for object classification based on the self-similarity of the object during motion [24]. The self-similarity of the human objects in the images shows a periodic variation because of the periodic nature of human gait. The algorithm developed by them consists of two parts. In the first part, the object of interest is segmented from the background based on motion. In the second part, the self-similarity of the object is computed as it moves in time. A time-frequency approach is then applied to analyse the periodicity of the self-similarity plots.

Stauffer and Grimson adopted a novel approach for the motion tracking [25]. They modelled the values of each of the pixels with mixture of Gaussians rather than modelling the values of all the pixels with a particular type of distribution. Based on the persistence and variance of each of the Gaussians of the mixture, they determined the Gaussians corresponding to the background colours. All the pixel values that do not fit the background distributions form the foreground. They used an on-line K-means approximation to update the model because EM algorithm would be very costly in such a situation where each of the pixel value is modeled with a Gaussian distribution. The foreground pixels are then segmented into regions by applying a two-pass connected components algorithm. After motion tracking, they classified the silhouettes and detected the unusual events. Shutler, Nixon, and Harris used statistical analysis by using temporal moments [26]. They proposed velocity moments based on the center of mass. Background was extracted using the temporal mode filter. The subjects were extracted by selective subtraction and region growing. The velocities were then calculated using the dense optical flow fields. The average velocity of each person was used to calculate the velocity moments up to the fourth order. They clustered the velocity moments to show that each subject forms a distinctive cluster.

Symmetry is a fundamental principle and most of the objects exhibit some form of symmetry. James et. al. proposed to use the symmetry of motion to distinguish between human and animal motion [27]. The symmetry information was estimated from the images using generalized symmetry operator which assigns a symmetry measure to each point in the image. They reported a recognition rate of 100% using silhouettes from SOTON (University of Southampton) database consisting of 16 sequences from 4 subjects. The recognition rate for University of California, San Diego (UCSD) database was slightly lower at 97.6% obtained by using silhouette data. The UCSD database used in their experiments consists of 42 sequences from 6 subjects.

BenAbdelkader, Cutler and Davis contended that planar dynamics of a walking person are encoded in 2D similarity plots between pair of images taken from the sequence of the walking person [28]. Assuming that camera is sufficiently far from the moving person, the camera projection becomes approximately orthographic with scaling. Under the orthographic projection and if the motion of the points are constrained to the planar motion, then the object dynamics are completely preserved in the projection up to a scale factor. Taking these assumptions, they first segmented the moving person from the background. The image templates were then scaled to the uniform height because the sizes may vary due to the depth variations and segmentation errors. A self-similarity plot is then obtained by correlation of each pair of images in the sequence. They used PCA to reduce the dimensionality of the input feature space. A recognition rate of 12% was achieved on Carnegie Mellon University (CMU) MoBo dataset when training on slow speed sequences and testing with moderate-speed sequences. However, the recognition rate was increased to 72% when both the training and testing was performed using slow sequences. A recognition rate of 76% was reported for the fast sequences.

To benchmark the performance of gait recognition techniques, a Baseline algorithm was presented in [29] by Philips et. al. The Baseline algorithm used the correlation between the silhouettes as a feature to represent gait. The gait sequences were segmented and the similarity measure based on the maximum correlation between the gallery and probe silhouettes was used. The paper also described the Gait Challenge (GC) database in detail and seven probe sets were given to assess the performance in different recording conditions.

Sunderesan, Chowdhury and Chellappa developed a general framework for recognition of humans using gait [30]. This framework is based on the HMM model. The framework assumed that the individual transitions among N discrete states during a walk cycle. An adaptive filter was used to detect the cycle boundaries. The framework is independent of the feature vector and can be adapted to different feature sets. The statistical nature of the HMM makes the model robust. They used binary images of the foreground after the background subtraction as feature vector. The experimental evaluation was done using GC database consisting of 75 subjects and 7 different probe sets. They achieved 99% CMS for probe A which dropped to 18% for probe G. The variation in results using different similarity measures was also reported.

In [31], Foster et.al. extracted the silhouettes by applying the chroma-key subtraction in conjunction with a connected component algorithm. After getting the silhouettes, they applied different area masks to the images and calculated the area under these masks. The area history for the different masks was thus obtained which carry the gait information. The area vectors from all the masks were then concatenated together and form the gait feature vector. Experiments were performed on the SOTON database. It was observed that the area vectors relating to the horizontal masks gave much higher discrimination than the vertical masks. They achieved a recognition rate of 76.6% by combining all the area vectors.

A subspace approach based on the matrix representation of gait data was proposed by Xu at. al. [32]. Traditionally, the image matrix is concatenated into a single dimensional vector to apply PCA and Linear Discriminant Analysis (LDA). The well-known curse of dimensionality due to large dimension compared to much smaller number of samples give rise to errors. The proposed matrix based coupled subspace analysis and discriminant analysis with tensor representation is an attempt at resolving the dimensionality issue. They achieved a significant performance increase over the Baseline algorithm. A CMS of 89% was achieved for probe A at rank 1 compared to 73% for the Baseline algorithm. Ioannidis et.al. designed three new feature extraction methods for gait recognition [33]. Two methods described as radial integration transform and circular integration transform are based on radon transform. Their third approach for feature extraction was based on weighted Krawtchouk moments. The depth information can also be incorporated if available. The recognition results were the highest for the Krawtchouk moments followed by radial integration transform and circular integration transform on GC database. They also used a feature fusion scheme based on genetic algorithm to improve the recognition performance. An improvement of 1-8% was obtained using all three types of features.

Yang et. al. decomposed gait energy image using Gabor wavelet kernels with 5 different scales and 8 orientations [34]. The feature vector was constructed using the Gabor phase and LDA was applied to reduce the dimension of the feature space. Comparative performance on GC database showed that Gabor phase possesses more discriminatory power than Gabor magnitude. An average CMS of 62.25% was achieved using Gabor phase compared to 51.88% for magnitude. Multi linear PCA (MPCA) was developed by Lu et. al. in [35]. MPCA was introduced to apply on the 3D gait data directly by representing it as tensors. The application of subspace projection directly to 3D gait tensor data mitigates the famous curse of dimensionality problem. It also preserves structural information which is lost when data is vectorized for processing with traditional PCA and LDA. The tensor data was first normalized to make all tensors equal dimension. MPCA is then applied to obtain Eigen tensors. Classification was performed using different distance functions. The GC database was used for performance evaluation. The average recognition performance of 54% and 76% was obtained at rank 1 and rank 5 respectively. This is a significant improvement over Baseline algorithm performance of 42% and 79% at rank 1 and rank 5 respectively.

Chen et. al. proposed a layered time series model which is a two level model combining HMM and dynamic texture model [36]. The gait cycle was first partitioned into temporally adjacent clusters of equal number of frames. Frieze feature and wavelet feature were then extracted from these clusters. Individual linear dynamic texture models were trained for each cluster that represent the states of the HMM. The evaluation was done using CASIA gait dataset B consisting of 124 subjects recorded from 11 views [37]. Wavelet features outperformed the frieze features in their experimental analysis. An average recognition rate of 95.7% was obtained using layered time series model technique which was higher than that of dynamic texture model and HMM results of 58.6% and 93.9% respectively. Wang et. al. modified the gait energy image and constructed chrono gait image to include temporal information [38]. After gait period detection, they used local information entropy to obtain the gait contour from the silhouette images. Synthetic chrono gait images were also constructed to avoid over fitting due to smaller number of real chrono gait images. LDA and PCA were applied for dimensionality reduction. A comprehensive experimental evaluation was reported using 3 major gait databases. An average CMS value of 48.64% and 66.81 was achieved at rank 1 and rank 5 respectively using all 12 probe sets of GC database. These results did not show marked improvements over related gait energy image method and were only marginally higher.

IV. MISCELLANEOUS METHODS

The traditional approach to human gait recognition is to construct some form of feature template and then apply pattern recognition methodology to compare these templates. The features are generally extracted from the silhouette sequences recorded from the side view using single camera. There are some works reported in literature that have departed from this traditional paradigm.

A channel coding method based on distributed source coding principles was adopted for human gait recognition by Argyropoulos et al. [39]. The framework is different from the traditional pattern recognition approach that is used for feature matching in gait recognition works. They experimented with features extracted using radial integration transform, circular integration transform and Krawtchouk moments. The gait features are then coded using SlepianWolf encoder implemented by using a systematic low density parity check encoder. In the authentication stage, the decoder decodes the code words using belief propagation. The correct code word is output if the error in the probe code word is within the error correction capability of the decoder and the identity is verified. A performance gain of 10% to 30% was achieved for all the experiments compared to the Baseline algorithm. In [40], Shakhnarovich, Lee, and Darrell developed a view normalization method for multi-view integrated face and gait recognition. The technique involves the computation of an image-based visual hull from a set of monocular views. This computed visual hull is then used to construct virtual views for tracking and recognition. Canonical viewpoints are constructed by examining the 3-D structure, appearance, and motion of the moving person. The centroid of the silhouette is determined and used to divide the whole silhouette into 7 regions. An ellipse is then fitted to each of the regions and features are extracted from these regions in every frame. The mean and standard deviation of these features over time are collected together to form the gait feature vector.

The idea of using more than one view to extract gait features has been attempted in several works such as the one reported in [41]. The use of frontal view video instead of the usual side view for gait recognition was also reported in some works. In [42], Goffredoat.el. used frontal view camera image sequence for gait recognition. After calculating the gait period, 3D gait volume was constructed using silhouettes from one gait cycle. The feature vector composed of 3D central moments of the gait volume and some scale dependent gait features including the number of frames for one gait cycle and the silhouette’s height and width maximum increment. They performed experiments on 3 data sets including CASIA-A and CASIA-B data. A correct classification rate of 91% and 97.92% was obtained for CASIA-A and CASIA-B respectively. Frontal view gait recognition was also tried in research reported in [43].

The quality of silhouettes is very critical for any gait recognition system and it is very hard to extract robust features from noisy silhouettes [44]. Liu and Sarkar performed silhouette reconstruction to remove noise and shadows. A population HMM was trained using manually specified silhouette data. The states of HMM represent the stances and the transition probabilities capture the motion dynamics between the stances. Statistical shape model called the eigen-stance gait model was constructed for each stance using manual silhouettes. Each frame was later matched with these stance subspaces using the already learned population HMM. The silhouettes were reconstructed by projecting it on the matched eigen-stance model. The experimental evaluation showed that the performance of the Baseline algorithm actually dropped when manual silhouettes were used. This surprising result indicates that the quality of the silhouettes does not always explain the drop in performance especially in case of variation in surface and time between probe and gallery sets.

IV. CONCLUSION

A brief overview of representative works in model based and appearance based gait recognition was provided. It is noted that in certain cases simpler techniques have produced much better results than those achieved by a lot complex and sophisticated methods. The quality of data and noise has always been considered a culprit responsible for errors and low efficiency. It was interesting to note that in one detailed study, it was found that the recognition results actually dropped when cleaner silhouettes were used. This may be the result of other variables affecting the performance of the system.

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