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Survey on Human Gait Recognition Using Patch Distribution Feature

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Abstract: *Detecting and locating object in digital image has become one of the most important applications for industrial use. Human identification by gait has created a great deal of interest in computer vision community due to its advantage of not easily seen recognition at a relatively far distance. The human gait is an important biometric feature for human identification. This paper provides a comprehensive survey of recent developments on gait recognition approaches. Individuals have distinctive and special ways of walking style. Here each gait energy image (GEI) is represented as a set of local augmented Gabor features, which concatenate the Gabor features extracted from different scales and different orientations together with the X–Y coordinates. This technique has been developed years ago but improvement of it is still requiring in order achieving the targeted objective in more efficiently and accurately. Detection of object from a complex background image uses the various techniques. The techniques used such as color processing which is used as filtering to eliminate the unrelated color or object in the image, shape detection is also used where it will use the edge detection method.*

Keywords*:* *Gait, Silhouette, Action Error*

1. Introduction

There is an increasing research interest in human identification in controlled environments such as airports, banks, and car parks. The human gait is an important biometric feature for human identification in such video-surveillance-based applications because it can be perceived unobtrusively from a medium to a great distance. In the view of biomechanics, individuals have distinctive and special ways of walking. Results from the field of psychology also demonstrated the ability for humans to distinguish human motion from other motion patterns, recognize friends and recognize gender, the direction of motion. The most recent psychological study has further demonstrated that humans can indeed recognize people by their gait. The existing methods for human gait recognition can be divided roughly into two categories: model-based and appearance-based approaches. In model-based approaches the human body structure is characterized using the model parameters fitted based on the extracted features. The parameters can be dynamic parameters e.g. the stride length and speed or static body parameters e.g., the size ratios of various body parts. In appearance-based approaches which employ a compact representation to characterize the motion patterns of the human body and have demonstrated better performance on the common databases.

2. History of Gaitrecognition

The pioneers of scientific gait analysis were Aristotle On the Gait of Animals and much later in 1680, Giovanni Alfonso Borelli also called *De Motu Animaliu)*. In the 1890s, the German anatomist Christian Wilhelm Braune and Otto Fischer published a series of papers on the biomechanics of human gait under loaded and unloaded conditions. With the development of photography and cinematography, it became possible to capture image sequences that reveal details of human and animal locomotion that were not noticeable by watching the movement with the naked eye. Eadweard Muybridge and Étienne-Jules Marey were pioneers of these developments in the early 1900s. For example, serial photography first revealed the detailed sequence of the horse "gallop", which was usually misrepresented in paintings made prior to this discovery.

Although much early research was done using film cameras, the widespread application of gait analysis to humans with pathological conditions such as cerebral palsy, Parkinson's disease, and neuromuscular disorders, began in the 1970s with the availability of video camera systems that could produce detailed studies of individual patients within realistic cost and time constraints. The development of treatment regimes, often involving orthopedic surgery, based on gait analysis results, advanced significantly in the 1980s. Many leading orthopedic hospitals worldwide now have gait labs that are routinely used to design treatment plans and for follow-up monitoring.

Development of modern computer based systems occurred independently during the late 1970s and early 1980s in several hospital based research labs, some through collaborations with the aerospace industry.[4] Commercial development soon followed with the emergence of commercial television and later infrared camera systems in the mid-1980s.

3. Gait Analysis

The gait analysis consists of two steps. First we do classification into one of the three gait types, i.e. walking, jogging, or running. Next we calculate the duty-factor *D* based on the silhouettes from the classified gait type. This is done to maximize the likelihood of correct duty-factor estimation. Fig.1. Illustrates the steps involved in the gait type analysis. Note that the silhouette extraction, silhouette description, and silhouette comparison all process single input frame at a time whereas the gait analysis is based on a sequence of input frames.

To get a robust classification of the gait type in the first step we combine three different types of information. We calculate an *action error E* for each action and two associated weights: *action likelihood α* and *temporal consistency β*. The following subsections describe the gait analysis in detail starting with the action error and the two associated weights followed by the duty-factor calculation

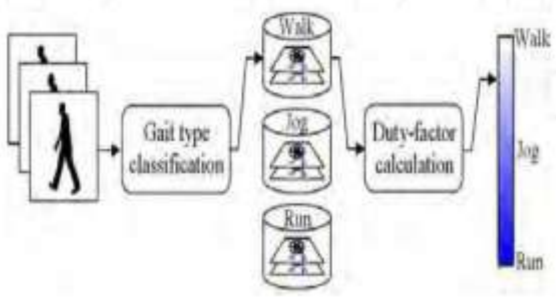

Fig1. *An overview of the gait analysis.*

The figure shows the details of the block "Gait analysis"

3.1 Action Error

The output of the silhouette comparison is a set of distances between the input silhouette and each of the database silhouettes. These distances express the difference or error between two silhouettes. Fig. 2. Illustrates the output of the silhouette comparison. The database silhouettes are divided into three groups corresponding to walking, jogging, and running, respectively. We accumulate the errors of the best matches within each group of database silhouettes. These accumulated errors constitute the *action error E* and corresponds to the difference between the action being performed in the input video and each of the three actions in the database, see Fig. 3.

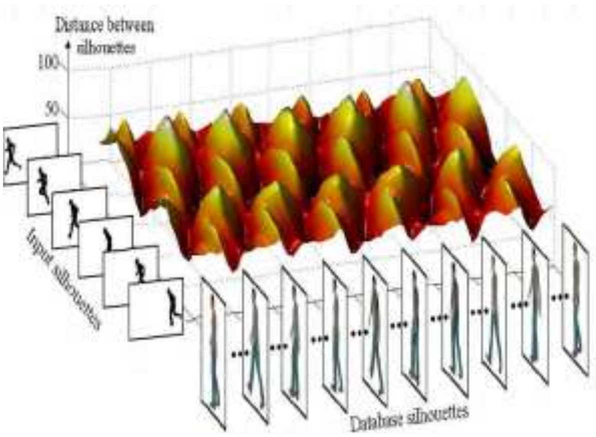

Fig. 2. *Illustrates the silhouette comparison output.*

The distances between each input silhouette and the database silhouettes of each gait type are found (shown for walking only). 90 database silhouettes are used per gait type, i.e. T=30.

3.2 Action Likelihood

When silhouettes of people are extracted in difficult scenarios and at low resolutions the silhouettes can be noisy. This may result in large errors between the input silhouette and a database silhouette, even though the actual pose of the person is very similar to that of the database silhouette. At the same time, small errors may be found between noisy input silhouettes and database silhouettes with quite different body configurations (somewhat random matches). To minimize the effect of the latter inaccuracies we weight the action error by the likelihood of that action. The action likelihood of action *a* is given as the percentage of input silhouettes that match action *a* better than the other actions. Since we use the minimum action error the actual weight applied is one minus the action

likelihood:

$$\beta_a = 1 - \frac{n_a}{N}$$

Where n_a is the number of input silhouettes in a sequence with the best overall match to a silhouette from action *a*, and *N* is the total number of input silhouettes in that video sequence.

This weight will penalize actions that have only a few overall best matches, but with small errors, and will benefit actions that have many overall best matches, e.g. the running action in

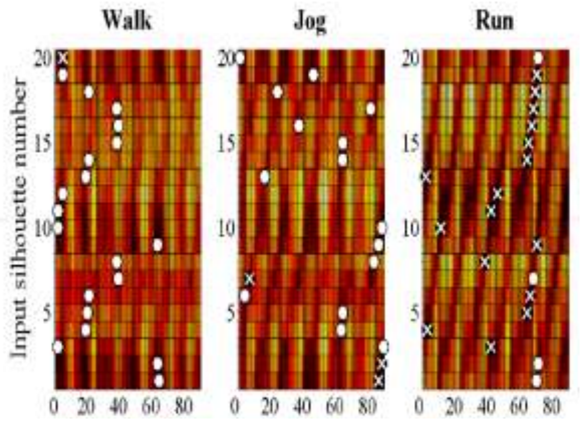

Fig. 3. *Database silhouettes numbers*

Fig. 3. Shows the output of the silhouette comparison of Fig. 2. Is shown in 2D for all gait types (dark colors illustrate small errors and bright colors illustrate large errors). For each input silhouette the best match among silhouettes of the same action is marked with a white dot and the best overall match is marked with a white cross. The shown example should be interpreted as follows: the silhouette in the first input frame is closest to walking silhouette number 64, to jogging silhouette number 86, and to running silhouette number 70. These distances are used when calculating the action error. When all database silhouettes are considered together, the first input silhouette is closest to jogging silhouette number 86. This is used in the calculation of the two weights.

3.3 Temporal Consistency

When considering only the overall best matches we can find sub-sequences of the input video where all the best matches are of the same action *and* in the right order with respect to a gait cycle. This is illustrated in Fig. 3. Where the running action has great temporal consistency (silhouette numbers 14-19). The database silhouettes are ordered in accordance with a gait cycle. Hence, the straight line between the overall best matches for input silhouettes 14 to 19 shows that each new input silhouette matches the database silhouette that corresponds to the next body configuration of the running gait cycle. Sub-sequences with correct temporal ordering of the overall best matches increase our confidence that the action identified is the true action. The temporal consistency describes the length of these sub-sequences. Again, since we use the minimum action error we apply one minus the temporal consistency as the weight *β*a:

$$\beta_a = 1 - \frac{m_a}{N}$$

where m_a is the number of input silhouettes in a sequence in which the best overall match has correct temporal ordering within action *a*, and *N* is the total number of input silhouettes in that video sequence.

Our definition of temporal consistency is rather strict when you consider the great variation in input silhouettes caused by the unconstrained nature of the input. A strict definition of temporal consistency allows us to weight it more highly than action likelihood, i.e. we apply a scaling factor *w* to *β* to increase the importance of temporal consistency in relation to action likelihood

$$\beta_a = 1 - W\frac{m_a}{N}$$

3.4 Gait-Type Classification

The final classifier for the gait type utilizes both the action likelihood and the temporal consistency as weights on the action error. This yields:

Action = arg min ($E_{a,}$, α_a, β_a)

where *E*a is the action error, *α*a is the action likelihood, *β*a is the weighted temporal consistency.

3.5 Duty-Factor Calculation

As stated earlier the duty-factor is defined as the fraction of the duration of a stride for which each foot remains on the ground. Following this definition we need to identify the duration of a stride and for how long each foot is in contact with the ground.

A stride is defined as one complete gait cycle and consists of two steps. A stride can be identified as the motion from a left foot takeoff (the foot leaves the ground) and until the next left foot takeoff accordingly a step can be identified as the motion from a left foot takeoff to the next right foot takeoff. Given this definition of a step it is natural to identify steps in the video sequence by use of the silhouette width. From a side view the silhouette width of a walking person will oscillate in a periodic manner with peaks corresponding to silhouettes with the feet furthest apart. The interval between two peaks will (to a close approximation) define one step . This also holds for jogging and running and can furthermore be applied to situations with people moving diagonally with respect to the viewing direction. By extracting the silhouette width from each frame of a video sequence we can identify each step (peaks in silhouette width) and hence determine the mean duration of a stride *t*s in that sequence. For how long each foot remains on the ground can be estimated by looking at the database silhouettes that have been matched to a sequence. We do not attempt to estimate ground contact directly in the input videos which would require assumptions about the ground plane and camera calibrations. For a system intended to work in unconstrained open scenes such requirements will be a limitation to the system.

Instead of estimating the feet's ground contact in the input sequence we infer the ground contact from the database silhouettes that are matched to that sequence. Since each database silhouette is annotated with the number of feet supported on the ground this is a simple lookup in the database. The ground support estimation is based solely on silhouettes from the gait type found in the gait-type classification which maximize the likelihood of a correct estimate of the ground support. The total ground support *G* of both feet for a video sequence is the sum of ground support of all the matched database silhouettes within the specific gait type.

To get the ground support for each foot we assume a normal moving pattern (not limping, Dragging one leg, etc.) so the left and right foot have equal ground support and the mean ground support *g* for each foot during one stride is *G*/(2*n*s), where *n*s is the number of strides in the sequence. The duty factor *D* is now given as *D*=*g*/*t*s. In summary we have

$$Duty\ factor\ D = \frac{G}{2.n_s.t_s}$$

Where *G* is the total ground support, *n*s is the number of strides, and *t*s is the mean duration of a stride in the sequence.

3.6 Gait Recognition System

System will identify unauthorized individual and compare his gait with stored sequences and recognize him. Background subtraction is the common approach of gait recognition. Background subtraction method is used to subtract moving objects and to obtain binary silhouette. Using background subtraction, pre-processing is done to reduce noise. Background subtraction techniques are also classified into two types: non-recursive methods and recursive methods. Non recursive technique uses sliding window approach for background subtraction. Recursive methods use single Gaussian method and Gaussian mixture model.

Gait recognition method contains two parts :
• Training part
• Testing part.

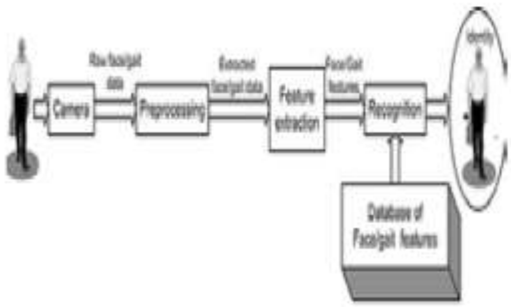

Fig 4. *The basic gait reorganization system*

Gait is a person's manner of walking. By this verification process, the system can identify the registered person. There are three different systems which can be categories as knowledge based, object based and biometric based. Knowledge based system is using normally password and pin number.

The object base is combination of knowledge based and object based such as smart card with pin code. But both password and smart card system can be steal or lost or forgotten to bring. To overcome these problems, the biometric based may have helped to solve the problems. It can be more reliable and is easy to interface with system. Nowadays biometric is the top research stages for the preventing purposes. Biometric gait recognition refers to verifying or identifying persons using their walking style.

The following is the flowchart of the Proposed Gait Recognition System:

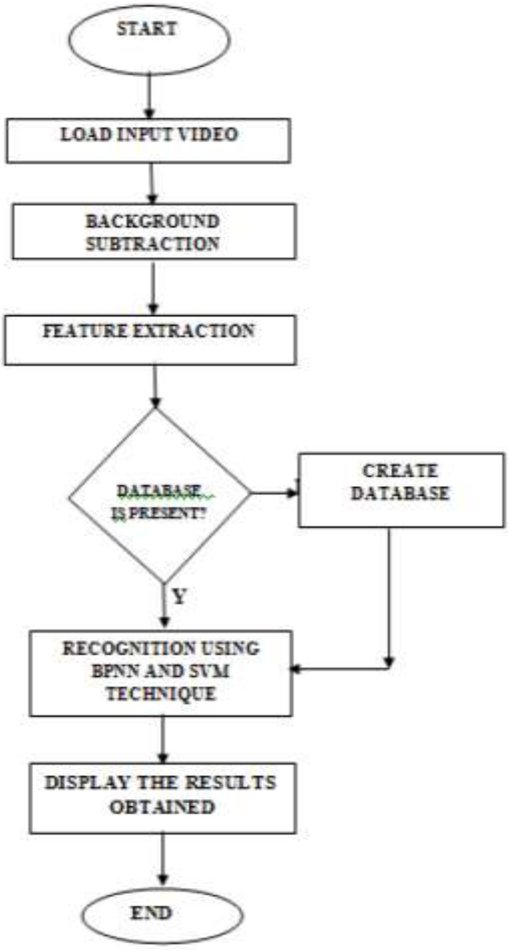

Fig 5. *The flowchart of the proposed gait recognition system*

Human recognition based on gait is relatively recent compared to other approach such as fingerprint, iris, facial etc. The biometric gait recognition can be grouped into three categories which are known as motion vision (MV) based, floor sensor (FS) based and wearable sensor (WS) based. So this paper is going to focus on motion vision based system for surveillance.

Model based approaches are difficult to follow in low resolution images also they have high computational complexity describes both walking and running. The use of double pendulum to describe the thigh and lower leg movement. Model based method construct human model to recover features describing gait dynamics such as stride and kinematics of joint angle.

Advantage of this approach is the ability to derive gait signature from model parameter and free from the effect of different clothing. Features used in this approach are insensitive to background cluttering and noise. Model based gait recognition system includes motion of thigh and lower leg rotation that

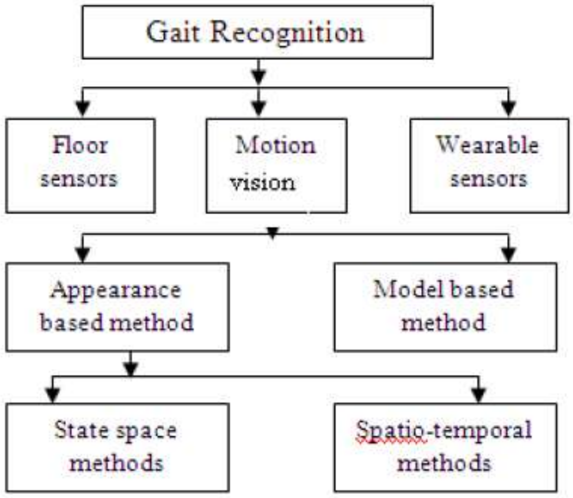

Fig 6. *The classification of gait recognition system*

Parameters used in this approach are height, distance between head and pelvis. Model free approach is easy to follow and has less computational complexity and this approach is best suited for real time systems. They used model free approach for gait recognition based on outermost contour. Background subtraction-Identifying moving objects from a video sequence are a fundamental task in Gait recognition. A common approach is background subtraction in which moving objects from background in the scene are identified. Pixels in the current frame that deviate significantly from the stationary background are considered to be moving objects.

4. Silhouette Representation

An important cue in determining underlying motion of a walking figure is temporal changes of the walker's silhouette. To make the proposed method insensitive to changes of color and texture of clothes, we use only the binary silhouette. Silhouette analysis based recognition system was proposed. In this, distance signal was the feature vector, which is obtained by calculating distance between each pixel and cancroids of the binary silhouette. In this paper, some of these limitations are overcome by taking combined features in the form of width and shape information of the binary silhouette of the person to be identified.

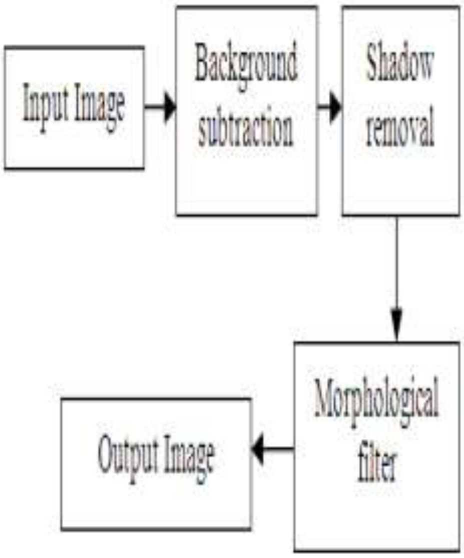

Fig7. *Silhouette representation*

First step of the proposed method is the extraction of foreground objects i.e., human and other moving objects are extracted from input video sequences. Gaussian mixture model is used for foreground object estimation in which an additional step of filtering by median filter is incorporated to remove noises. Moving target classification algorithm is used separate human being (i.e., pedestrian) from other foreground objects (viz., vehicles). Shape and boundary information is used for this moving target classification. Width vector of outer contour of binary silhouette and MPEG-7 ART (Angular Radial Transform) coefficients are taken as the feature vector. These extracted feature vectors are used to recognizing individuals. Hidden Marko Model (HMM) is used for recognizing persons on the basis of gait. Various parameters like distance between hand and distance between legs are calculated.

5. Feature Extraction

Feature selection is a crucial step in gait recognition. The feature must be robust to operating conditions and should yield good discriminability across individuals. Each gait sequence is divided into cycles. Gait cycle is defined as person starts from rest, left foot forward, rest, right foot forward, the stances during gait cycle. Gait cycle is determined by calculating sum of the foreground pixels. At rest positions this value is low. By calculating number of frames between two rest positions, gait cycle (period) is estimated.

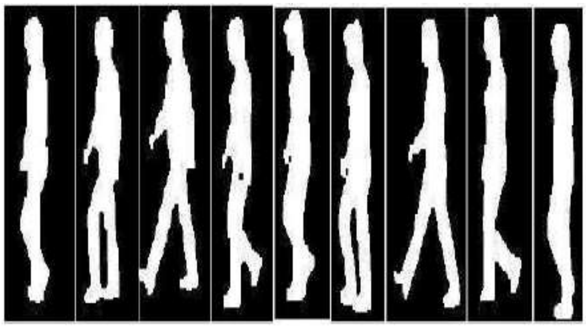

Fig8. *Stances during a gait cycle*

Two types of features are extracted, the height and the width of the silhouette.

6. Conclusion

The gait type of people that move around in open spaces is an important property to recognize in a number of applications, e.g. automated video surveillance and human-robot interaction. The classical description of gait as three distinct types is not always adequate and this chapter has presented a method for describing gait types with a gait continuum which effectively extends and unites the notion of running, jogging, and walking as the three gait types. The method is *not* based on statistical analysis of training data but rather on a general gait motion model synthesized using a computer graphics human model. This makes training (from different views) very easy and separates the training and test data completely. The method is designed to handle challenges that arise in an unconstrained scene and the method has been evaluated on different data sets containing all the important factors which such a method should be able to handle. The method performs well (both in its own right and in comparison to related methods) and it is concluded that the method can be characterized as an invariant method for gait description.

The method is further developed to allow video input from multiple cameras. The method can achieve real-time performance and a method for online adjustment of the background subtraction method ensures the quality of the silhouette extraction for scenes with rapid changing illumination conditions.

The quality of the foreground segmentation is important for the precision of the gait classification and duty-factor estimation. The segmentation quality could be improved in the future by extending the color based segmentation of the Codebook method with edge information directly in the segmentation process and furthermore including region based information. This would especially be an advantage in scenes with poor illumination or with video from low quality cameras. The general motion model used to generate training data effectively represents the basic characteristics of the three gait types, i.e. the characteristics that are independent of person specific variations. Gait may very well be the type of actions that are most easily described by a single prototypical execution but an interesting area for future work could be the extension of this approach to other actions like waving, boxing, and kicking.

The link between the duty-factor and the biomechanical properties of gait could also be an interesting area for future work. By applying the system in a more constrained setup it would possible to get camera calibrations and ground plane information that could increase the precision of the duty-factor estimation to a level where it may be used to analyze the performance of running athletes.

With the increasing demands of visual surveillance systems, human identification at a distance has recently gained more interest.Gait is a potential behavioral feature and many allied studies have demonstrated that it has a rich potential as a biometric for recognition. This paper has described a simple but effective method for automatic person recognition from body silhouette and gait. The combination of a background subtraction procedure and a simple correspondence method is used to segment and track spatial silhouettes of a walking figure.

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