Model-based Gait Recognition

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Synonyms

Knowledge-based gait recognition, Gait Models for Biometrics

Definition

Model-based Gait Recognition concerns identification using an underlying mathematical construct(s) representing the discriminatory gait characteristics (be they static or dynamic), with a set of parameters and a set of logical and quantitative relationships between them. These models are often simplified based on justifiable assumptions such as the system only accounts for pathologically normal gait. Such a system normally consists of gait capture, a model(s), a feature extraction scheme, a gait signature and a classifier (Figure 1). The model can be a 2- or 3-dimensional **structural** (or **shape**) **model** and **motion model** that lays the foundation for the extraction and tracking of a moving person. An alternative to a model-based approach is to analyse the motion of the human silhouette deriving recognition from the body's shape and motion. A gait signature that is unique to each person in the database is then derived from the extracted gait characteristics. In the classification stage, many pattern classification techniques can be used, such as the *k*-nearest neighbour approach.

The main advantages of the model-based approach are that it can reliably handle occlusion (especially self-occlusion), noise, scale and rotation well, as opposed to silhouette-based approaches.

Practical issues that challenge the model-based approach can be divided into two categories, which relate to the *system* and to the *person*. Some of the systems related challenges are viewpoint invariant, whilst those embedded in the person are the effects of *physiological* changes (such as aging, the consistency of gait at taken/enrolled at different time stamps), *psychological* (mood, whether this behaviour changes over time), and *external factors* (load, footwear and the physical environment).

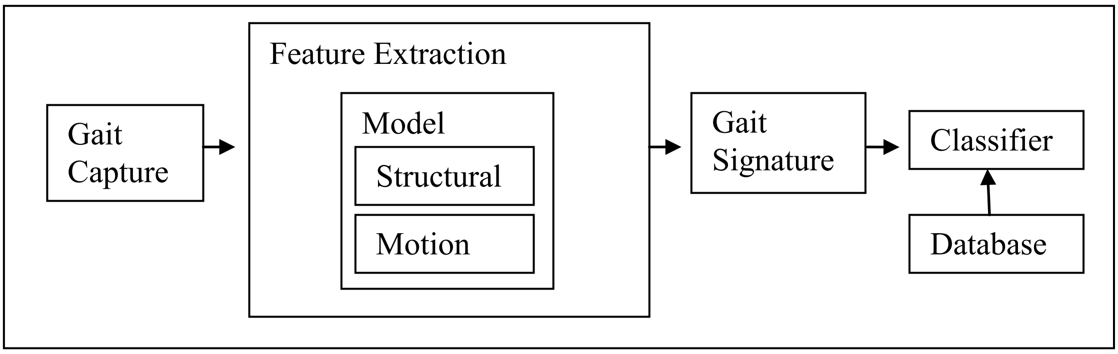


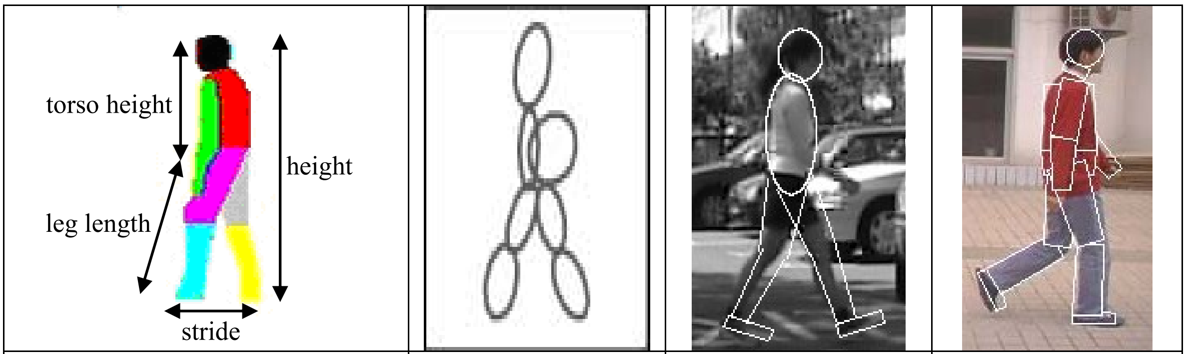
Figure 1: Components of a typical model-based gait recognition system.

Main Text

The first model-based approach to gait biometrics was by Cunado in 1997 [Cunado1, Cunado2], mainly motivated by its attractiveness of being able to reliably accommodate self-occlusion and occlusion by other objects, noise and low resolution. Also, most of the time, the parameters used within the model and their relationship can be understood, i.e. the mathematical construct itself may contain implicit/explicit meaning of the gait pattern characteristics. Though, it often suffers from high computational cost, this can be mitigated by optimisation tools or increased computing power. Gait sequences are usually acquired when the subject is walking in a plane normal to the image capture device since the side view of a moving person reveals most information, though it is possible to use other views.

Models

In a typical model based approach, often, a **structural model** and a **motion model** are required to serve as the basis for tracking and feature (moving human) extraction. These models can be 2- or 3- dimensional, though most of the current approaches are of 2-dimensional and have shown capability to achieve promising recognition results on large database. A structural model is a model that describes the topology or the shape of human body parts such as head, torso, hip, thigh, knee and ankle by measurements such as the length, width and position. This model can be made up of primitive shapes (cylinders, cones, and blobs), stick figures, or arbitrary shapes describing the edge of these body parts. On the other hand, a motion model describes the kinematics or the dynamics of the motion of each body part. Kinematics generally describe how the subject changes position with time without considering the effect of masses and forces, whereas dynamics will take into account the forces that act upon these body masses and hence the resulted motion. When developing a motion model, the constraints of gait such as the dependency of neighbouring joints and the limit of motion in terms of range and direction has to be understood.



(a) [Bobick]	(b) [Lee]	(c) [Wagg]	(d) [Wang]

Figure 2: Example body parameters that are used in structural models.

Bobick et al. used a structural model to recover static body and stride parameters (Figure 2a) determined by the body geometry and the gait of a person [Bobick]. Lee et al. fit ellipses to seven regions representing the human body (Figure 2b), then derived two types of features across time: mean and standard deviation, and magnitude and phase of these moment-based region features [Lee].

Cunado et al. proposed an early motion model based approach, based on the angular motion of the hip and thigh [Cunado1, Cunado2], where the angular motion of the hip and the thigh is described by a Fourier series. For this method, a simple structural model was used and the angular rotation is as defined in Figure (3). Although the motion model is for one leg, assuming that gait is symmetry, the other leg can be modelled similarly, with a phase lock of ½ period shift (Figure 4).

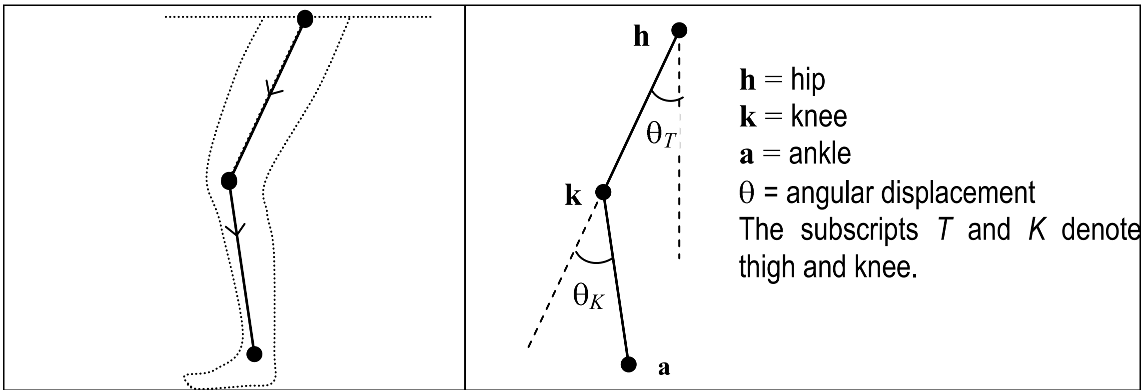


Figure 3: Structural model of a lower limb: upper and lower pendulum represents the thigh and the lower leg, respectively, connected at the knee joint.

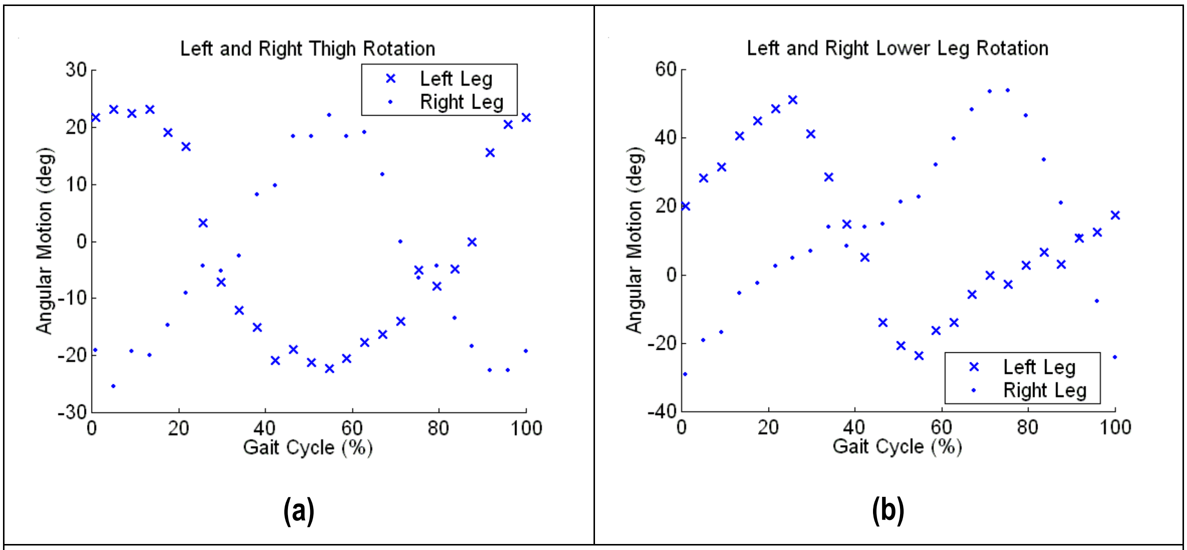


Figure 4: Thigh and lower leg rotation of the left and right leg.

The angular motion of the thigh can be modelled by

$$\theta = a_0 + 2\sum_{1}^{N}[b_k \cos k\omega - c_k \sin k\omega]$$

where N is the number of harmonics, ω is the fundamental frequency and a_0 is the offset. In application, the frequency data was accumulated from a series of edge detected versions of the image sequence of the walking subject. The gait signature was derived by the multiplication of the phase and magnitude component of the Fourier description.

Later, Yam et al. extended the approach to describe the hip, thigh and knee angular motion of both walking and running gaits first by an empirical motion model, then by an analytical model motivated by coupled pendulum motion [Yam]. Similarly, the gait signature is the phase-weighted magnitude of the Fourier description of both the thigh and knee rotation.

Bouchrika et al [Bouchrika] has proposed one of the latest motion model-based gait feature extraction using parametric form of elliptic Fourier descriptors to describe joint displacement.

$$\begin{bmatrix} x(t) \\ y(t) \end{bmatrix} = \begin{bmatrix} a_0 \\ b_0 \end{bmatrix} + \begin{bmatrix} \cos(\alpha & -\sin(\alpha \\ \sin(\alpha & \cos(\alpha \end{bmatrix} \begin{bmatrix} X(t) * S_x \\ Y(t) * S_y \end{bmatrix}$$

where α is the angle and S_x and S_y are the scaling factors. The joint trajectory is then fitted to the image sequence by optimising a_0, b_0, α, S_x and S_y; the motion model fit is implemented by the Hough Transform. To reduce the computational load, heel strike data is incorporated to reduce the complexity. The heel strike data is automatically extracted using corner information.

Wagg et al. (Figure 2c) and Wang et al. (Figure 2d) used a combination of both structural and motion model to tract and extract walking human figure [Wagg, Wang], where Wagg has introduced a self-occlusion model whilst Wang used the Condensation framework to aid feature extraction.

Feature Extraction

Here, segmentation of interested body parts of a moving human is performed, and extraction of static and/or dynamic gait characteristics. The feature extraction process normally involved model initialisation, segmentation and tracking (estimation) of the moving human from one image to the next. This is a significant step that extracts important spatial, temporal or spatial-temporal signals from gait. Feature extraction can then be carried out in a concurrent [Cunado1, Cunado2, Yam, Wang], or iterative/hierarchical [Wagg] manner.

A recent approach is used to illustrate operation [Wagg] and feature extraction can refine operation in model-based approaches. A conventional starting point of a gait cycle is heel strike at the stance phase, although any other stages within a gait cycle can be used. Earlier techniques determine the gait cycle manually, later, many have employed automatic gait cycle detection. A gait cycle can be detected by simply identifying the stance phase, if using a bounding box method, the width of the box has the highest value. Other alternatives are counting the pixels of the human figure, using binary mask (Figure 5) by approximating the outer region of the leg swing, so that sum edge strength within the mask varies periodically during the subject's gait and the heel strike being the greatest [Wagg].

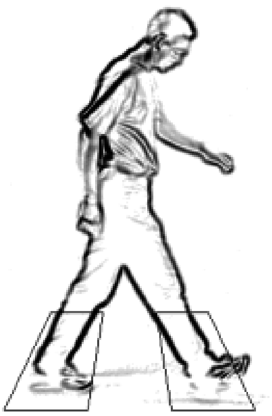


Figure 4: Binary mask to detect gait cycle.

Quality of Feature Extraction

A quality model configuration is defined as one that yields a high correlation between the model and the subject's image. Useful measures for computing model-image correlation include *edge correspondence* and *region correspondence* [Wang]. Edge correspondence is a measure of how closely model edges coincide with image edges, whilst the region correspondence is a measure of similarity between the image region enclosed by the model and that corresponding to the image of the subject. These two measures are to be used together as a high edge correspondence indicates that the model is closely aligned with image edges; however, it does not guarantee that the model matches the correct edges. If the initial model configuration is poor, or the subject is occluded, the match may be coincidental. For this reason, region correspondence is also required. Another measure is by a Pose Evaluation Function (PEF) which combines the boundary matching error and the region matching error to achieve both accuracy and robustness. For each pixel p_i in the boundary of the projected human model, the corresponding pixel in the edge image along the gradient direction at pixel p_i (*Figure 5*) is searched. In other words, the pixel nearest to p_i and along that direction is desired. Given that q_i is the corresponding pixel and that $\boldsymbol{F}_i$ stands for the vector $\overrightarrow{p_i q_i}$, the matching error of pixel p_i to q_i can be measured as the norm $\|\boldsymbol{F}_i\|$. Then the average of the matching errors of all pixels in the boundary of the projected human model is defined as the boundary matching error

$$E_b = \frac{1}{N}\sum_{i=1}^{N} \|\boldsymbol{F}_i\|$$

where N is the number of the pixels in the boundary.

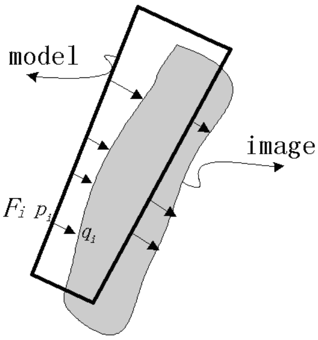
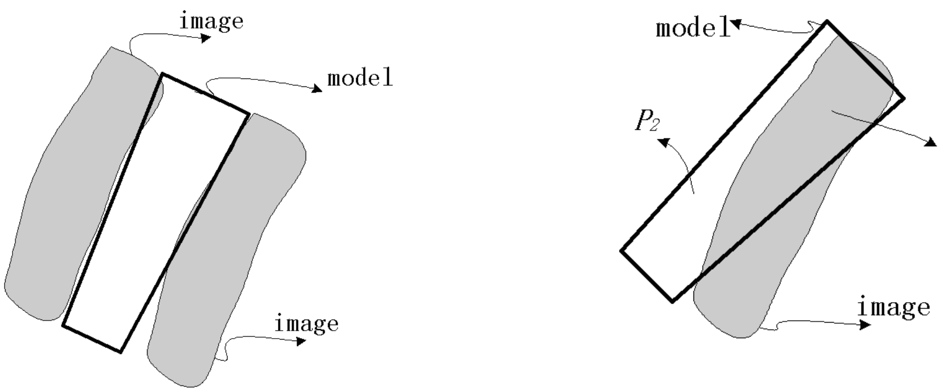


Figure 5: Measuring the Boundary Matching Error

In general, the boundary matching error can properly measure the similarity between the human model and image data, but it is insufficient under certain circumstances, such as an example given in *Figure 6a*, where a model part falls into the gap between two body parts in the edge image. Although it is obviously badly-fitted, the model part may have a small boundary matching error. To avoid such ambiguities, region information is further considered. *Figure 6b* illustrates the region matching. Here the region of the projected human model that is fitted into the image data is divided into two parts: P_1 is the region overlapped with the image data and P_2 stands for the rest. Then the matching error with respect to the region information is defined by

$$E_r = |P_2| / (|P_1| + |P_2|)$$

where $|P_i|, (i=1,2)$ is the area, i.e., the number of pixels in the corresponding region.



(a) a typical ambiguity: a model part falls into the gap between two body parts

(b) measuring region matching error

Figure 6: Illustrating the Necessity of Simultaneous Boundary and Region Matching

Recognition

A gait signature is a discriminatory feature vectors that can distinguish individual. These signatures have invariant properties embedded in a person such as stride length, person's height/width, gait cycle and self-occlusion, and that related to the imaging system such as translation, rotation, scale, noise and occlusion by other objects These signatures can be of static [Bobick], dynamic [Cunado2, Yam] or a fusion of static and dynamic [Wang, Wagg] characteristics of gait or with other biometrics [Kale, Shakhnarovich]. The fusion can happen either at the feature extraction stage or the classification stage. On the Southampton datasets of 115 subjects filmed indoors (in controlled conditions) and outdoors (with effects of shadows, background objects and changing illumination) Wagg's approach achieved an overall CCR of 98.6% on the indoor data and 87.1% on the outdoor data.

Conclusions and Outlook

Using a model is an appealing way to handle known difficulty in subject acquisition and description for gait biometrics. There is a selection of models and approaches which can handle walking and running. Clearly the use of a model introduces specificity into the feature extraction and description process, though this is generally at cost of increased competition. Given their advantages, it is then likely that model-based approaches will continue to play a part in the evolution of systems which deploy gait as a biometric. Currently, practical advantages of 3D approaches have yet to be explored and investigated. Given that human motion occurs in space and time, it is likely that much information is embedded within the 3D space. Further, 3D approaches may provide a more effective way to handle issues like occlusion, pose and view point. Therefore, 3D model-based gait recognition may be a good way to move forward.

Related Entries

Human Detection and Tracking, Human Body Modelling, Silhouette-based Recognition, Multi-modality.

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