Extracting Human Gait Signatures by Body Segment Properties

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Abstract

We describe a new method for extracting human gait signatures by topological analysis, using properties of body segments. The gait signature is extracted in three stages: extraction of the body contour by a thresholding and morphological filter; extraction of the leg angles based on regression analysis of contour data; and finding the body points guided by known anatomical knowledge. A 2D stick figure is used to represent the human body model, and trajectory-based kinematic features are extracted from the image sequences for describing and analyzing the gait motion. Also, the inherent periodicity in gait motion is analyzed by delay coordinates and a phase-space portrait. The utility of the proposed method is demonstrated in experiments, with comparison to medical data.

1. Introduction

The study of human gait has generated much interest in fields including biomechanics, robotics, computer animation, and visual surveillance. The human gait is known to be one of the most universal and complex of all human activities. It has been studied in medical science [1, 2, 3], psychology [4, 5], and biomechanics [6, 7, 8, 9] for decades. In computer vision, recognizing humans by gait has recently been investigated. As a biometric, human gait may be defined as a means of identifying individuals by the way they walk [10]. Using gait has many advantages over other biometrics such as fingerprints, most notably that it is non-invasive.

The human gait is a pattern of human locomotion and can be described by kinetic or kinematic characteristics [11]. Gait signatures are the most effective and well-defined representation method for kinematic gait analysis. The gait signatures can be extracted by motion information from human gait, and it is crucial in computer graphics, clinical applications, and human identification. In medical examination, gait motion measurement systems have used markers that represent the observed movement in the form of 3D trajectories that translate into kinematic variables such as body movements and joint angles [12]. However, using markers needs intrusive and expensive specialized hardware and requires contact with a subject.

This study aims to generate gait signatures by computer vision and to extract kinematic features for describing motion. To achieve this, we propose a new method for extracting the body points by using properties of body segments extracted using guidance by anatomical knowledge. A 2D stick figure is used to represent the human body model, and joint angles are calculated to describe the gait motion. The trajectory-based kinematic features are extracted from image sequences for analyzing the gait motion, and a delay-coordinate system and phase-space portrait are used for periodicity detection. Results show that the new approach works successfully, in comparison with medical data acquired by a marker system, and should therefore prove suited to the suggested application domains.

2. Human Gait and Body Segments

Human gait can be defined as a form of locomotion in which the body's centre of gravity moves alternately on the right side and left side. During walking, the human body functionally divides into the passenger and locomotor units. The upper body is a relatively passive passenger unit that rides on a locomotor unit. Each gait cycle is separated into two distinct periods: the stance and the swing phase. The stance phase is the entire period during which the foot is on the ground, and the swing phase begins as the foot is lifted from floor (toe-off). The normal distribution of the floor contact period is 60% for stance and 40% for swing [3]. Fig. 1 shows the phases of human gait cycle.

Human gait is a form of periodic motion, especially when walking laterally; hence we can predict human movement in a gait cycle. Murray [1] considers human gait as "a total walking cycle" - the action of walking can be thought of as a periodic signal. This assumes that the pattern of the motion is approximately sinusoidal in nature. The sinusoidal functions are basically all periodic

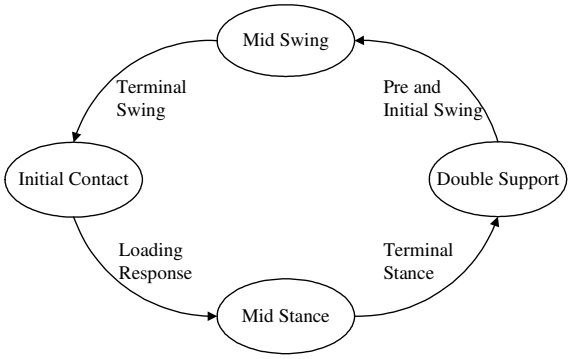
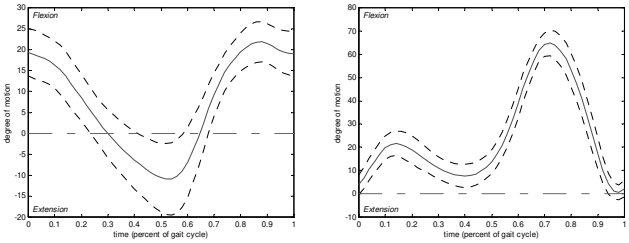


Figure 1. Human Gait Cycle

with periodic 2π. The motion period and gait frequency are the time taken by a step and the number of steps taken per second, respectively. Therefore, the human gait can be described as periodic motion if all the spatial-temporal parameters are repeated after p steps, where p is a gait period.

However, the human gait in kinematic analysis is usually characterized by the joint angles between body segments and their relationships to the events of the gait cycle [8, 9]. The joint angles are more commonly expressed as flexion and extension. Flexion occurs when two body segments change their relative position and decrease the angle between them, i.e. upward motion of the foot towards the tibia. Similarly, extension is the return from flexion, i.e. when the angle between the two segments increases [3, 13]. Figs. 2(a) and (b) show the mean and standard deviations, by medical data from anatomical markers in limb segment [8], for joint angle of the thigh and knee motion during one gait cycle.



(a) Thigh Angles vs. Time (b) Knee Angles vs. Time

Figure 2. Normal Range during Free Walking

On the other hand, the analysis of human motion often requires knowledge of the properties of body segments. The dimensions of various body segment-links callipered from cadavers were extensively studied [7, 14]. Their anatomical literature presented a stick figure in which the lengths were shown as a percentage of body height. The results of this study have been used in dynamic models for animating human motion. Fig. 3 shows body segment properties represented as a percentage of body height, H. The mean dimensions of body height can be used to determine topological position of each body part in human

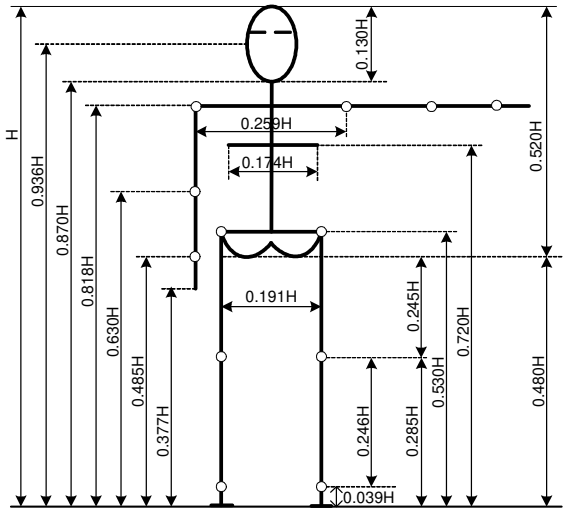


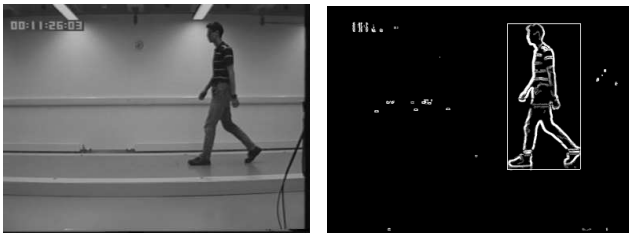
Figure 3. Body Segment Properties [7]

figures as such to guide search for the human head and toe, given that humans have a head, neck, shoulder, chest, waist, pelvis, knees, and ankles in known topology.

3. Extracting the Human Gait Signatures

3.1. Extracting the Body Contour

To extract the human body in a real scene image, background subtraction [15] using an edge difference image with noise filtering is employed to handle any change in illumination. The histogram projection profiles are analyzed to estimate the position of a human body in the edge difference image. Figs. 4(a) and (b) show a real scene image with 384×288 gray-scale and detected human body region by prior knowledge such as size and shape.



(a) Gray-Scale Image (a) Body Detection

Figure 4. Detecting the Human Body

Thresholding and morphology is then used to extract the contour of a detected human body. A thresholding method based on similarity measures between the background and the current image is used. Let $I_{rb}(x, y)$ and $I_{rc}(x, y)$ be the brightness of a pixel with coordinates (x, y) in raw background image (I_{rb}) and raw current image (I_{rc}). Then, the similarity $\Theta(x, y)$ at coordinates (x, y) is calculated by

$$\Theta(x, y) = | I_{rb} - I_{rc} | \quad (1)$$

Similarity values close to zero imply a high probability of

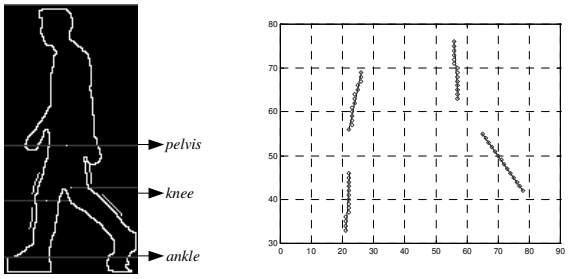
being background; conversely, large values of similarity imply high probability as an object. Therefore, the binary image $I_{bi}(x, y)$ is thresholded as

$$I_{bi}(x,y) = \begin{cases} 1 & \text{if } \left(\Theta(x,y) > \tau\right) \wedge \left(I_{rc}(x,y) > \eta\right) \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

where τ is a tolerance value, and η denotes a global threshold value. Finally, the body contour is determined by arithmetic subtraction followed by dilation and erosion. Thresholding is a simple image segmentation method, and erosion will remove the outer layer of pixels from an object. However, this method is very effective and useful for small and low-resolution images.

3.2. Extracting the Leg Angles

The leg angles are extracted from border data of the body contour by linear regression. To extract the border data, the expected vertical position of the pelvis, knees and ankles is derived by using the known body properties showing in Fig. 3. The knees have the largest movement of all parts of the leg. Therefore, five horizontal lines around the expected knee position are scanned. The knee position is determined by the minimum distance from the *x*-axis in a left walking direction or maximum distance from the *x*-axis in a right walking direction. In addition, the vertical position of a knee in the rear region should be equal to or higher than the vertical position of a knee in the front region. Consequently, the border data for the thigh are collected by pixel positions between the knees and the pelvis at the front and rear boundaries. The boundary data for shin are collected from positions between knees and ankles. Fig. 5(a) shows the expected joint positions and extracted border pixels from the body contour determined by our new approach. Fig. 5(b) shows the extracted border data with lines selected by least-squares analysis superimposed. Data near joint positions is masked from these calculations.



(a) Body Contour (b) Border Data and Line Fitting

Figure 5. Extracting Gait Angles by Least Squares

The thigh and shin angles can be calculated by linear regression using the border data. The angles $\theta_{jnt,k}$ of joint *jnt* at image frame *k* can be approximated by the slope of the lines in linear regression equation as [16]

$$\theta_{jnt,k} = \sum_{i=1}^{n}(y_i - \bar{y})(x_i - \bar{x}) \Big/ \sum_{i=1}^{n}(x_i - \bar{x})^2 \quad (3)$$

where n is the number of the points and $jnt \in$ *thigh, shin, knee*. Also, certainty factor (CF) $\gamma_{jnt,k}$ of the angle $\theta_{jnt,k}$ can be determined by the correlation coefficient as

$$\gamma_{jnt,k} = \left| \sum_{i=1}^{n}(y_i - \bar{y})(x_i - \bar{x}) \Big/ \sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2 \sum_{i=1}^{n}(x_i - \bar{x})^2} \right|. \quad (4)$$

In general, a segmented image is highly susceptible to noise in the object boundary, and the border data can include spurious pixels. Therefore, a weighted moving average is employed to reduce the influence of angles measured in noisy frames as

$$\theta_{jnt}(n) = \sum_{k=n-q}^{n+q}(\gamma_{jnt,k} \bullet \theta_{jnt,k}) \Big/ \sum_{k=n-q}^{n+q}\gamma_{jnt,k} \quad (5)$$

where q is a size of moving window, here set to 2. The weighted moving average is an effective method to smooth out a time series data.

3.3. Extracting the Gait Signatures

To extract the gait signature from the body contour, the expected horizontal scan position (y_i) of each body part is guided by using the known properties of body segments in Fig. 3. In the upper body region including head, neck, shoulder, and chest, the horizontal coordinate is calculated from two border points as

$$x_{center} = x_s + \left(x_l - x_s\right) / 2 \quad (6)$$

where x_s and x_l represent the horizontal position of the first and the last pixels on the scan line respectively. The waist and pelvis coordinate is approximated by the coordinates of the shoulder and chest as

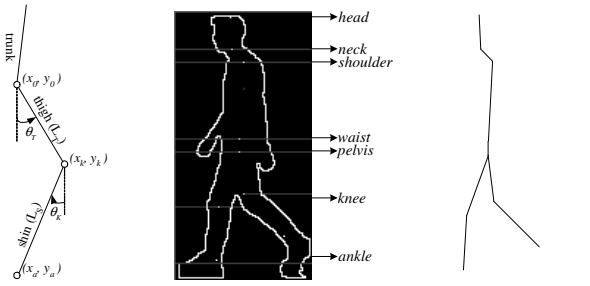
$$x_{waist} = x_{pelvis} = x_{chest} + \frac{(x_{chest} - x_{shoulder})}{(y_{chest} - y_{shoulder})}(y_{waist} - y_{chest}). \quad (7)$$

Finding the knees and ankles requires a more sophisticated algorithm than finding the upper body components. These points can be determined by the leg angles, which extracted from border data of the body contour by linear regression as in previous section. That is, the knee and ankle points are calculated by

$$x_{ka}, y_{ka} = \left[x_i + L_{ts}\cos(\theta + \phi) \quad y_i + L_{ts}\sin(\theta + \phi)\right] \quad (8)$$

where ϕ is the phase shift, x_i and y_i are the coordinates of a previously established position such as pelvis, and L_{ts} is the length of the thigh or shin guided by using known properties of body segments (see Fig. 6(a)).

There are nine coordinates (body points) determined by topological analysis and linear regression in human body: (x_{head}, y_{head}), (x_{neck}, y_{neck}), $(x_{shoulder}, y_{shoulder})$, (x_{waist}, y_{waist}), (x_{pelvis}, y_{pelvis}), (x_{knee1}, y_{knee1}), (x_{knee2}, y_{knee2}), (x_{ankle1}, y_{ankle1}), and (x_{ankle2}, y_{ankle2}). Figs. 6(b) and (c) show the body points determined by this approach and the gait



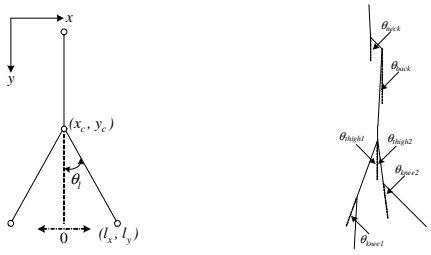
(a) Leg Joints (b) Body Points (c) Gait Signature

Figure 6. Body Points and Gait Signature

signature obtained by connecting the nine coordinates. Now we can calculate the six angles which are associated with these positions: θ_{neck}, θ_{back}, θ_{thigh1}, θ_{thigh2}, θ_{knee1}, and θ_{knee2}. In general, the angle $\theta_{l,k}$ of location (l_x, l_y) at frame k can be calculated by

$$\theta_{l,i} = \tan^{-1}\left(\left(l_x - x_c\right)/\left(l_y - y_c\right)\right). \quad (9)$$

Fig. 7(a) shows the definition of position (l_x, l_y) and the angle θ. By definition [7, 8], the joint angles are relative, thus the relative angles in each joint were computed from the measured values of the angles. The definition of joint angles in gait signature is shown in Fig. 7(b).



(a) θ_l at (l_x,l_y) (b) Joint Angles

Figure 7. Joint Angles in the Gait Signature

On the other hand, trajectories of gait signature contain kinematic characteristics on human moving. The kinematic characteristics include linear and angular position, their displacements and the time derivatives, notably the linear and angular velocities and accelerations. As a feature, the gait velocity v_k at frame k is calculated by

$$v_k = (x_k - x_{k-1})/\Delta t. \quad (10)$$

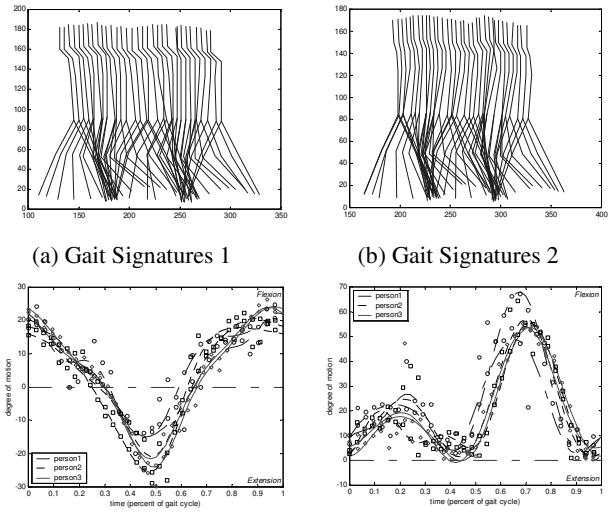
Also, the angular velocities $\omega_{l,k}$ at frame k, given an inter-frame time Δt (1/25 sec, for Figs. 9), are

$$\omega_{l,k} = \left(\theta_{l,k} - \theta_{l,k-1}\right) / \Delta t. \quad (11)$$

The trajectories are basically vector-valued function at each frame k of an image sequence, and they are periodic that is the important component of a gait motion.

4. Results

In the experiments, three different humans and two image-sequences with around 32 consecutive images for each sequence are used for analyzing a gait cycle. A set of



(a) Gait Signatures 1 (b) Gait Signatures 2

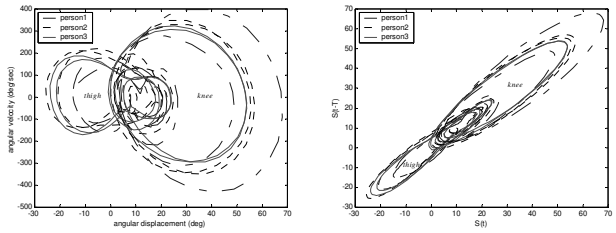
(c) Thigh Angles vs. Time (d) Knee Angles vs. Time

Figure 8. Gait Motion during One Gait Cycle

the gait data extracted from image sequences provides potentially valuable time-dependent patterns as a gait time series. We represent the human body structure in the gait signature by a 2D stick figure model with six joint angles. Thus, human gait motion can be described in a compact form, as a sequence of the joint parameters.

The extracted gait signatures during one gait cycle shown in Figs. 8(a) and (b). Figs. 8(c) and (d) show the time series data of the relative joint angles obtained from the gait signatures during one gait cycle. In figures (c) and (d), the points are values of the angles that computed by using Eqns. 3 and 5, and the lines are interpolated by trigonometric polynomials. These are consistent with medical data of Figs. 2(a) and (b) and differ between subjects. As in the medical studies [1, 3], the thigh and knee at initial contact are flexed about 20° and 5° from the vertical, respectively. During the loading response, the thigh position is relatively stable, possible losing 2°~3° of flexion, and the thigh progressively extends at same rate after mid stance. Also, peak extension of knee is attained slightly before the end of the swing phase.

Most human locomotory motions can be characterized as having a periodic component. The phase-space portrait is a useful method in periodic motion analysis [17]. Figs. 9(a) and (b) show the phase-space portraits of angular velocity vs. displacement and each value of the time series of angles ($\theta_{l,i}$) versus a time delayed version, by plotting ($\theta_{l,i}$, $\theta_{l,i-T}$) for fixed delay T=1/25 second. The delay plot [18] also represents periodic motion because the same orbit is described, and the plot exhibits symmetry. The small curves on the left region show the thigh motion, whilst the large curves on the right show the knee motion, and we can observe periodicity in human gait motion. Cleary, the knee motion is characterized by a large range of motion. This



(a) Phase-Space Portrait (b) Delay Plot

Figure 9. Periodicity Analysis for Gait Motion

transforms Figs. 8(c) and (d) to reveal the periodic nature of gait. In the figures, two clusters have very little difference between the curves from two different image sequences, but the other one does not match as well as those of the other subjects due to their particular style of clothing. We can also predict a gait motion using the delay plot and phase-space portrait. In addition, the limit-cycle attractor [17] of each motion can be determined in delay coordinate and in phase-space. Again, these are consistent with known medical analysis.

One of the most distinctive characteristics of human gait is the fact that it is individualistic. To identify human by gait motion, an enhanced back-propagation neural network algorithm is employed as a classifier, and a small number of gait features are used as input data. We have manly used kinematic features such as average linear and angular velocities selected based on heuristic knowledge. The features are extracted from the image sequence during a time periodic. Though the recognition rate here was 100% we have used a very small set of data for classification, thus making meaningful comparisons of recognition performance impossible. Naturally we seek to extend the analysis in future, both in number of subjects and hence to other techniques.

5. Conclusions

We have described a new method for extracting the gait signatures and kinematic features for analyzing and identifying the gait motion, guided by known anatomy. The gait signature is extracted from the human body contour by determining the scan position using known body topology. A 2D stick figure is used to represent the human body model, and trajectory-based kinematic features such as linear and angular velocities are extracted from the image sequences. Delay coordinates and phase-space portrait show the inherent periodicity in human gait. Then, an enhanced back-propagation neural network algorithm is employed to classify the gait features. As such, this new approach appears to recognize the body's structure and its motion. In future we seek to clarify the technique in terms of application capability as well as analyzing a larger database of subjects.

Acknowledgment

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