Automated Markerless Analysis of Human Gait Motion for Recognition and Classification

Jang-Hee Yoo and Mark S. Nixon

We present a new method for an automated markerless system to describe, analyze, and classify human gait motion. The automated system consists of three stages: i) detection and extraction of the moving human body and its contour from image sequences, ii) extraction of gait figures by the joint angles and body points, and iii) analysis of motion parameters and feature extraction for classifying human gait. A sequential set of 2D stick figures is used to represent the human gait motion, and the features based on motion parameters are determined from the sequence of extracted gait figures. Then, a *k*-nearest neighbor classifier is used to classify the gait patterns. In experiments, this provides an alternative estimate of biomechanical parameters on a large population of subjects, suggesting that the estimate of variance by marker-based techniques appeared generous. This is a very effective and well-defined representation method for analyzing the gait motion. As such, the markerless approach confirms uniqueness of the gait as earlier studies and encourages further development along these lines.

Keywords: Human motion, gait analysis, biometrics.

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I. Introduction

Human gait is known to be one of the most universal and complex form of all human activities and has been described and analyzed more than any other total movement [1]-[3]. Moreover, human gait analysis has many challenging issues because the highly flexible structure and self-occlusion of the human body mandate complicated processes for the measurement and analysis of its motion [4]. Gait motion is defined as a form of locomotion in which the body's center of gravity moves alternately on the right side and left side. It requires the simultaneous involvement of all lower limb joints in a complex pattern of movement [1], [5]. Furthermore, each person appears to have his or her own characteristic gait pattern. There is much evidence from psychophysical experiments [6], [7] and medical and biomechanical analysis [1], [2], [8], [9] that gait patterns are unique to each individual. In computer vision, recognition of humans by their gait has recently become a challenging area [10]-[15].

As a biometric, human gait is defined as a means of identifying individuals by the way they walk [3]. Using gait has many advantages over other biometrics, such as fingerprints, iris, and face recognition, most notably because it is non-invasive and available at low resolution. There are two major approaches to gait recognition in computer vision [3], [15]. The first is model-based, where the subject's movement is described by a body model. In this approach, a body model is fitted to the human in every frame of the walking sequence, and kinematic parameters are generally measured on the body model as the model deforms over the walking sequence. An alternative method is to apply a model-free (or holistic) description to the set of images. Model-free approaches use features based on the motion or shape of subjects. Thus, extracting features which truly discriminate among groups is a critical task in identification or recognition of humans because improperly extracted features frequently lead to a low classification rate and require complex classification algorithms.

On the other hand, gait measurement is crucial in clinical applications, biomechanical analysis, computer graphics, and human identification. At present, most available measurement systems are based on external markers which are attached to key anatomical positions of the human body [16], [17]. Accordingly, trajectories of the gait motion are observed by each marker's 3D position, and the trajectories translate into kinematic variables, such as body movements and joint angles [18]. Using markers can help us acquire precise motion information, but such markers require intrusive specialized hardware and subject contact. Therefore, with advances in computing power, markerless methods have recently been investigated for use in computer vision. However, many markerless motion capture systems have been studied for tracking and extracting objects, though not for biomechanical or recognition purposes [19]. To enable greater application capability, an effective markerless system is an essential requirement.

In this paper, we propose a new approach to an automated markerless system for describing, analyzing, and classifying human gait by computer vision techniques without subject contact or intervention. The human body and its contour are extracted from the image sequences from one of the largest video gait databases, which comprises digital video (DV) recordings of walking subjects. Then, the gait figure, represented by a planar stick figure with six joints and eight sticks is extracted from the body contour data. In the sequence of gait figures, motion parameters are calculated and measured to characterize the human gait patterns. Also, features based on the motion parameters are extracted and selected from the gait sequence by statistical analysis. In addition, a *k*-nearest neighbor (*k*-NN) classifier is used to derive introductory classification results, demonstrating recognition capability. As such, the new system aims to derive measures which can supplement those of established biomechanical significance, in part demonstrated by classification capability.

II. Representing Human Gait Motion

An automated markerless analysis of human motion can be achieved by a vision-based method in complex image sequences. This method normally does not require any specialized hardware attached to a human body. The only input needed is a video recording of the subject. The vision-based method involves segmenting the body parts, tracking the movement of joints, and recovering the body structure in an image sequence [20]. This low-level processing requires

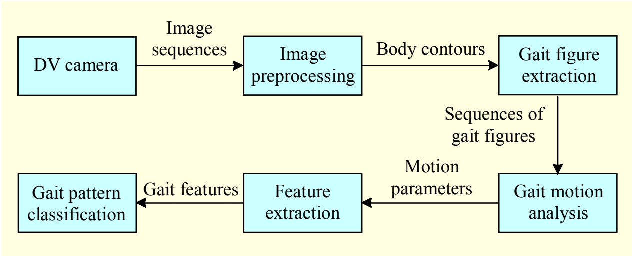

Fig. 1. Automated markerless system for analyzing human gait.

complicated vision computing on a high-performance computer system. The markerless system consists of three stages. In the first stage, the images are preprocessed by brightness and morphological analysis which in turn derives a body contour from the image data. This is a binary image wherein the contour points are white, and the remainder are black. In the second stage, gait figures are extracted from the contour data to recover the human movement from a non-invasive image sequence. In the final stage, the motion is analyzed from within a sequence of moving gait figures. This is represented as joint angles and vertex points, which are together used for gait classification. Figure 1 shows the procedure of the markerless gait analysis system used within this study.

The simplified 2D stick figure model, with six joint angles, is closely related to the observation that human motion is essentially the movement of the human skeleton; thus, the stick figure can be described as a collection of body segments and joint angles with various degrees of freedom [11], [20]. Also, the horizontal center of mass which is approximated by two border points at the chest region is used as a gait symmetry point to detect the gait cycle. According to biomechanical analysis, the torso, that is, the upper body part, is moving in both the plane of progression and the frontal plane as an inverted pendulum which rotates about the hip joint [2]. Therefore, the upper body's speed varies a little, being fastest during the double support phases and slowest in the middle of the stance and swing phases [17]. In addition, the center of mass of the upper body will keep the maximum distance from the front foot at initial contact, end of terminal stance, or terminal swing, and it has minimum distance from the front foot at end of mid-stance or mid-swing. Consequently, important gait phases can be detected from the peaks and troughs in a time series of the gait symmetry points, which are essentially a measure of the width of the subject's contour.

1. Video-Based Gait Database

Our database, hereafter referred to as the SOTON database [10], comprises two forms of indoor data (under controlled

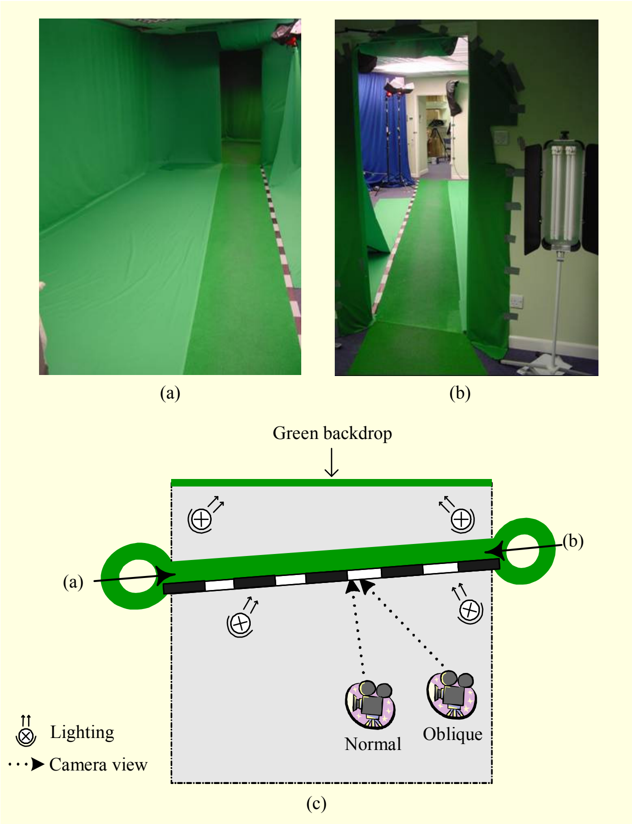

Fig. 2. Indoor walking track used in SOTON database: (a) front view, (b) far view, and (c) layout and views.

lighting with a special background) and one of outdoor data (without lighting or background control). The first form of indoor data is of a subject constantly walking on a treadmill. The second form is that of a subject walking along a specially designed track shown in Fig. 2. The use of track and treadmill for the same subject allows for analysis of any influence on gait by the treadmill, but that is not done here as the evaluation concerned the indoor track data only. As can be seen in the figure, a chroma-key laboratory with controlled lighting conditions gives the special purpose background for the indoor treadmill and track data. Green was chosen to be the chroma-key color because it contrasts well with the clothing of the majority of the subjects. Also, the outdoor data used a similar track layout with a greater distance between subject and camera. An image sequence contains only a single subject walking at normal speed and was acquired at 25 fps with 720×576 color pixels from good quality progressive scan DV cameras. All subjects in the database are filmed at a fronto-parallel view (where the walking path is normal to the plane of the camera view) or at an oblique angle. Each subject has at least four image sequences, and each image sequence contains at least one gait cycle, together with images of the background without the subject present, and other supporting data, such as

Fig. 3. Images from SOTON database: (a) indoor track image and (b) outdoor image.

the subject's height and weight.

The SOTON database contains more than 100 different subjects and was mostly acquired from young and healthy university students during the summer. Figure 3 shows sample images from the SOTON database. Given the use of the green chroma-key background, human body extraction from the image sequences can be easily achieved by subtracting an image of the background. Here, we used a thresholding method based on similarity measures of color and brightness between the background and the object. Thresholding is a simple image segmentation method, and erosion will remove the outer layer of pixels from an object. If dilation can be said to add pixels to an object or to make it bigger (thickening), then erosion makes an object smaller by removing pixels (thinning). Therefore, an object's contour (or outline) can be obtained just by subtracting the results of dilation and erosion.

2. Extracting Human Gait Figures

The analysis of human motion often requires knowledge of the properties of body segments. The dimensions of various body segment-links callipered from cadavers have been extensively studied [21], [22]. To extract body points from a contour image, the skeleton data with body segment properties is used to guide the initial estimate. For a body height H, the initial estimate of the vertical position of the neck, shoulder, waist, pelvis, knee, and ankle was set by a study of anatomical data to be 0.870H, 0.818H, 0.530H, 0.480H, 0.285H, and 0.039H, respectively. The gait skeleton can be simply obtained by two border points of each body segment p with a range constraint as

$$x_{s,p} = (x_{b,p} + x_{e,p}) / 2, \tag{1}$$

where x_b and x_e represent the horizontal position of the first and the end pixels on the horizontal line, respectively. In the images from the SOTON database, an estimation of a primary gait skeleton is highly susceptible to difficulty by the movement of the arm and foot. Therefore, to reduce the effects of noise (outlier), the estimated mean value and standard deviation of each body segment position are used to select a skeleton point as

$$x'_{s,p} = \begin{cases} x_{s,p} & \text{if } \left(x_{s,p} \subset \bar{x} \pm \alpha \cdot \sigma\right) \\ \varnothing & \text{otherwise,} \end{cases} \quad (2)$$

where σ is standard derivation of $x_{s,p}$, and α is a parameter ($1 \le \alpha \le 3$) which depends on the body segments and tuned by analysis of training data. Figures 4(a) and (b) show the gait skeleton and the noise-removed skeleton data.

Now we can calculate the body angles from the skeleton data by linear regression. The angles θ_p of body segment p are approximated by using the slope of the lines by linear regression as

$$\theta_p = \tan^{-1}\left(\sum_{i=1}^{n} \left(x_i - \bar{x}\right)^2 \Big/ \sum_{i=1}^{n} \left(y_i - \bar{y}\right)\left(x_i - \bar{x}\right) \right), \quad (3)$$

where n is the number of the skeleton points in the body segment. The points are determined successively, starting with the top of the head and finishing with the feet. Each body point (many of which are joint positions) is calculated by using the joint angle and the size of each body segment as

$$x_p, y_p = \left[x_i + L_p \cos(\phi + \theta_p) \quad y_i + L_p \sin(\phi - \theta_p) \right], \quad (4)$$

where ϕ is the phase shift, x_i and y_i are the coordinates of the previously established position for that body point, and L_p is the length of body segments [22] which are approximated by anatomical segments' data based on measured image body height. As shown in Fig. 4(c), a 2D stick figure with the nine body points (whose position is shown by the small circles) is derived from the skeleton data of each body segment by linear regression. These include the shoulder, waist, knee, and ankle points as routinely used in gait analysis.

The body points around double support phases (initial contact, terminal stance, and terminal swing) are clearly extracted, but the points around single support phases are not extracted as well as those around the double supports. Therefore, a motion tracking method between double supports is used to extract body points at the lower limbs. To track knees and ankles, the most forward skeleton points around the knee region and the rear-most skeleton points around the ankle region are considered. The skeleton points by each body segment are sorted as

$$\boldsymbol{x}_{\text{knee}} = \left\{ x \mid x_i < x_{i+1} \right\} \text{ and } \boldsymbol{x}_{\text{ankle}} = \left\{ x \mid x_i > x_{i+1} \right\}. \quad (5)$$

The proper size of body segments is also guided by anatomical knowledge. The knee and ankle points for tracking are given by their mean value as

$$\boldsymbol{x}_s = \left\{ x_i \mid i = m, \ldots, n \right\} \text{ and } \bar{\boldsymbol{x}}_s = \text{mean}(\boldsymbol{x}_s), \quad (6)$$

where m and n are data indices, here set to 3 and 5, respectively.

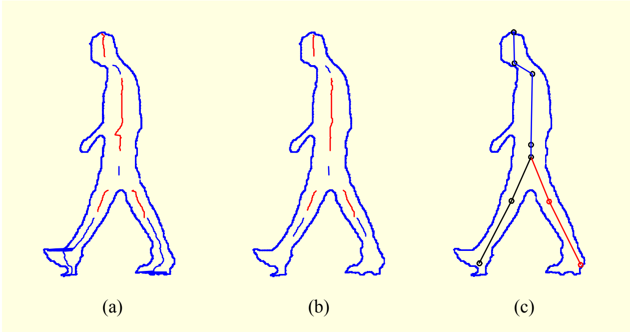

Fig. 4. Extracting stick figure at a key-frame: (a) gait skeleton, (b) outliers removed, and (c) stick figure.

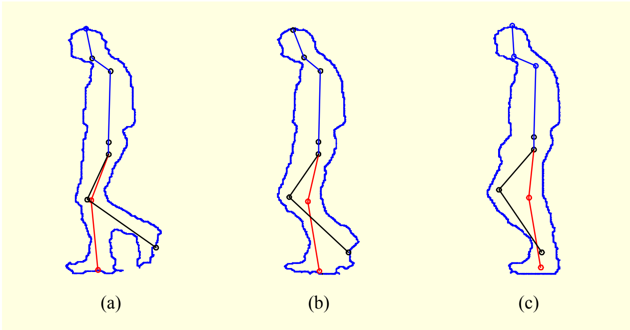

Fig. 5. Stick figure at a crossover of the legs: (a) t–1, (b) t, and (c) t+1.

Walking left, the knee position around a single support can be determined by the minimum distance from x-axis, and the ankle position can be determined by the maximum distance from x-axis. The forward displacement Δx_t at frame t is calculated as

$$\Delta x_t = \bar{x}_t - \bar{x}_{t-1}. \quad (7)$$

In normal walking, the knee and ankle positions are moving in the direction of walking, hence the forward displacement should be measured as a positive value.

Finally, the body points at frame t are calculated by (3) and (4) using the new angle values and segment sizes of thigh and shin. In addition, functional or physical constraints exist in human gait motion. During the gait cycle, the other foot is in contact with the floor (and does not move forwards). Also, the knee angle should be equal to or smaller than the hip angles. The crossover of the two legs is performed on two single support (mid-stance and mid-swing) points during one gait cycle. Figure 5 shows an example of body point extraction by using the gait constraints. In the figure, the crossover at the knee is detected during the three frames of a single support, and ankle crossover is started after a single support. These constraints are used to improve the robustness of the method.

3. Motion Parameters of Human Gait

The trajectories of gait figures contain the general gait parameters (also known as the temporal and spatial parameters), such as stride length, cycle time, and speed, and provide a basic description of the gait motion [2]. The period of the gait motion is determined by number of frames during one gait cycle in image sequence, and the frame rate of the SOTON database was 25 frames/s. The cycle time and the gait speed are given by

$$cycle\_time(\mathrm{s}) = \frac{gait\_period(\mathrm{frames})}{frame\_rate(\mathrm{frames/s})}, \tag{8}$$

$$speed(\mathrm{m/s}) = \frac{stride\_length(\mathrm{m})}{cycle\_time(\mathrm{s})}, \tag{9}$$

where the stride length can be directly estimated from the physical dimensions of the image plane. The stride length is determined by the coordinates of the forward displacements of the gait figures during one gait cycle.

In addition, the kinematic parameters are usually characterized by the joint angles between body segments and their relationships to the events of the gait cycle. In the gait figures, the joint angles can be determined from the coordinates of the body points. By definition, the joint angles are measured as one joint relative to another, so the relative angles in each joint are derived from the extracted angle values [2]. In normal walking, the torso of a human body can be considered to be almost vertical. Thus, the relative hip angle is the same as that of the extracted value, and the relative knee angle θ_{Knee} can be defined from the extracted hip angle θ_{H} and knee angle θ_{K} as $\theta_{\mathrm{Knee}}=\theta_{\mathrm{H}}-\theta_{\mathrm{K}}$. The trajectories of the gait figure contain many kinematic characteristics on human movement including linear and angular position, their displacements, and the time derivatives, notably the linear and angular velocities and accelerations. Basically, the trajectories are a vector-valued function at each frame t of an image sequence, and they are periodic as in gait motion.

Typically, statistical analyses of the gait relationships use continuous curves of the time series data measured over the gait cycle. Medical study [8] has shown that the pattern of gait motion is approximately sinusoidal in nature. Trigonometric functions are naturally suited to estimating a gait curve from time series data. Accordingly, an assumed functional relationship between periodic gait motion and time can be modeled by interpolation of trigonometric polynomials. Also, further gait motion can be predicted by the periodicity of this interpolation model. An n-th-order trigonometric-polynomial interpolant function is

$$y_n(t) = a_0 + a_n\cos(2\pi nt) + \sum_{k=1}^{n-1}\left[a_k\cos(2\pi kt) + b_k\sin(2\pi kt)\right], \tag{10}$$

where the a_0, a_n, a_k, and b_k are unknown curve-specific coefficients. As $n\to\infty$, $y_n(t)$ tends to the Fourier series. The interpolation of much (equally-spaced) data by trigonometric polynomials can make for very accurate results.

III. Experimental Results

In the experiments, 100 different subjects (16 females and 84 males) with seven image sequences of each subject from the SOTON indoor track database, a total of 700 image sequences (≅19,534 images), are used. A set of gait data extracted from image sequences provides potentially valuable time-dependent pattern as a gait time series. The stick figures extracted from an image sequence during one gait cycle are shown in Fig. 6(a), and its forward displacement at hip, knee, and ankle is shown in Fig. 6(b). The forward displacement of joints is consistent with medical data by Inman's analysis [1], and it is an important component for showing quality of the extracted gait figures.

In the image plane of the SOTON indoor track database based on the viewing geometry and viewing distance, one pixel

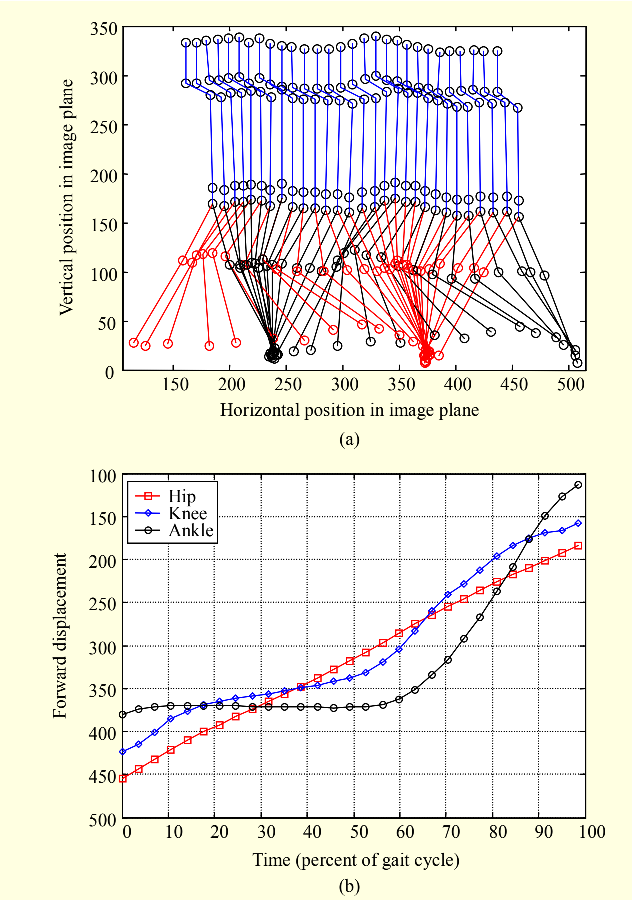

Fig. 6. Example of gait motion during one gait cycle: (a) sequence of stick figures and (b) forward displacements.

Table 1. General gait parameters from SOTON database.

Age level	Gender	Cadence (steps/min)	Cycle time (s)	Stride length (m)	Speed (m/s)
Children	Male	109-130	0.92-1.10	1.36-1.52	1.23-1.65
	Female	-	-	-	-
Adults	Male	103-116	1.03-1.17	1.57-1.76	1.42-1.62
	Female	110-122	0.98-1.10	1.43-1.62	1.38-1.56

was approximated by the physical dimension 0.5 cm×0.5 cm, thus the dimension of the human body and its motion parameters can be simply estimated by the coordinates of the body points and forward displacements in the gait figures. Table 1 shows the variation of the general gait parameters, which are obtained. In the table, the speed is based on estimated stride length, and all parameters belong to the range of the expected value shown in a medical study [17]. In practice, the speed is likely to be close to the upper limit as the majority of the subjects in the SOTON database might have a preponderance of young subjects in the sample. Also, the markerless measurement is a non-impeding method, which is enabling them to walk in a natural and more relaxed manner. Accordingly, a person may achieve a greater stride length than with a marker-based approach.

In addition, human gait motion can be described in a compact form, as a sequence of the joint parameters. Figure 7 shows the results of measuring relative joint angles obtained from 100 different subjects during one gait cycle. In the figures, the lines are the curves that result from using 4th-order trigonometric-polynomial interpolants in (10). As in medical studies [2], [5], [8], the hip and knee at initial contact are flexed by about 25° and 5° from the vertical, respectively. During the loading response, the hip position is relatively stable, possibly losing 2° to 3° of flexion, and the hip progressively extends at a similar rate after mid-stance. Also, albeit by a different technology, the variance in Figs. 7(c) and 7(d) would appear to be smaller than for Winter's analysis [2]. These results concern 100 subjects with seven sequences of each subject, a total of 700 sequences, that is, a much larger volume of data than in Winter's analysis. Further, in this analysis, subjects were not supervised and carried no markers, allowing for relaxed walking patterns. This is also reflected in the small number of traces that lie outside of the general trend. However, it can clearly be seen that the general trend is followed by most of the traces, suggesting that earlier analyses could be informed by this new approach.

However, one of the most distinctive characteristics of human gait is the fact that it is individualistic. To classify the gait patterns, a simple k-NN algorithm is employed as a

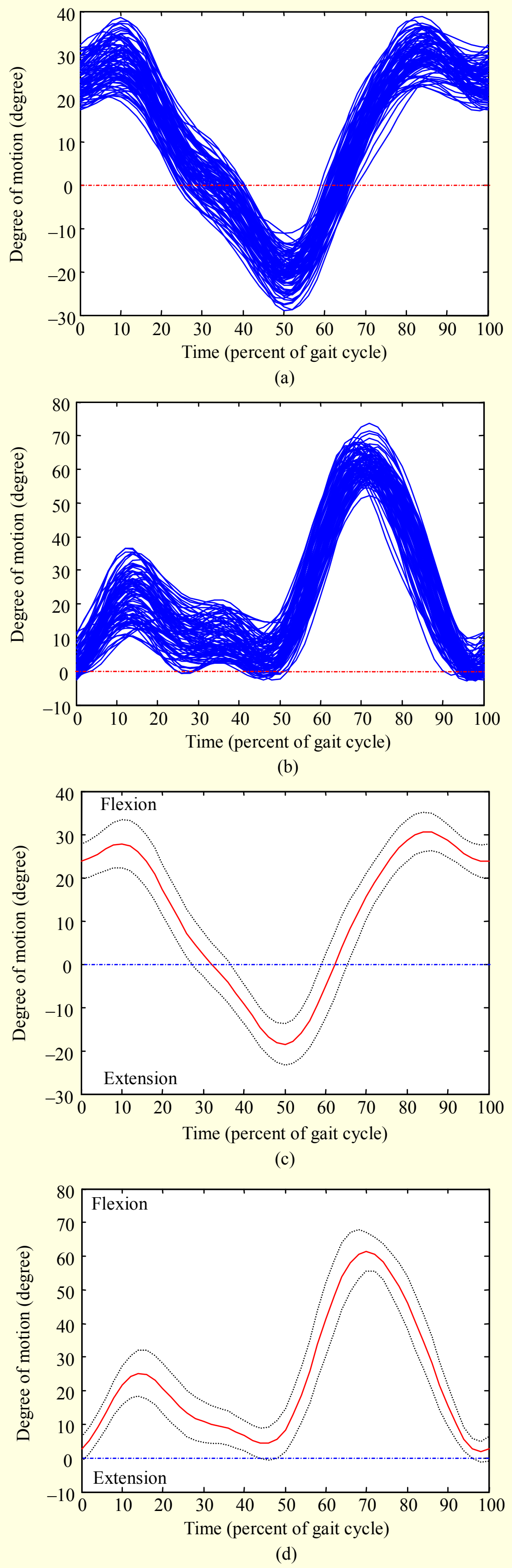

Fig. 7. Relative inter-segment angles from SOTON database: (a) hip angles vs. time, (b) knee angles vs. time, (c) hip angles vs. time with mean (solid line) and variance (dotted lines), and (d) knee angles vs. time with mean and variance.

Table 2. Classification results by *k*-NN classifier.

No. of subjects	No. of feature vectors		CCR (%)		
	Training	Test	*k*=1	*k*=3	*k*=5
30	150	30	96.7	93.3	96.7
60	300	60	91.7	86.7	85.7
100	500	100	84.0	80.0	82.0

classifier applied to a feature space comprised of 10 features based on the motion parameters: body height, cycle time, stride length, speed, average joint angles, variation of hip angles, the correlation coefficient between the left and right leg angles, and the center coordinates of the hip-knee cyclogram. Undoubtedly, a more sophisticated classifier would be prudent, but the interest here is to examine the genuine discriminatory ability of the features. A total of the 500 feature vectors extracted from the front four of the seven sequences and their means for each of 100 different subjects are used as the training samples. Also, a total of 100 feature vectors extracted from the means of the remaining three of the seven sequences for each of 100 different subjects are used as the test samples.

Table 2 shows the classification results by number of subjects. As can be seen in the table, the new method achieved up to a 96.7% correct classification rate (CCR) for 30 subjects and 84.0% CCR for 100 subjects, which compares well with other studies [3]. In recognition studies, the variation of the cluster of measurements for repeated same-subject exposure is called the within-class variance. The between-class variance describes the variation between different subjects. Recognition can be achieved via distance in the feature space (the *k*-NN is the mode class of the *k* nearest subjects in feature space) so long as the within-class variance is less than that of the between-class variance. Reduction in recognition capability with increase in *k* (the number of neighbors considered) reflects the clusters of features overlap, but this is not always the case here.

Also, a back-propagation neural network algorithm is applied to the SOTON indoor database for identifying humans by their gait. The 10 selected gait features for each subject are used as input data, and the numbers of hidden nodes and output nodes are set to 28 and 13, respectively. The neural networks are trained until recognition on the training data reached 100%, thus the classification rates for each group of the training sets were 100%. The neural network approach achieved a recognition rate of up to 90% for 30 subjects. In practice, other studies [3] have clearly confirmed classification capability on this database, using more features by area masks, a symmetry operator, velocity moments, and principal component analysis than given here to achieve a similar classification rate (97.3% CCR for 28 subjects) to our approach gives. Although the recognition rate does not reach 100%, the results show that people are unique in their walking patterns, in line with earlier biomechanical suggestions, and buttressing other similar results. In future, we will concentrate both on improving of the gait figures (to reduce clutter) and on developing of the efficient feature vector with evaluation and experiments using real-world data to expose further gait as a biometric.

IV. Conclusion

We have described an automated markerless gait analysis system using computer vision techniques. To achieve this, a stick figure representation has been extracted by combining a statistical approach and topological analysis guided by anatomical knowledge. In the sequence of stick figures, the motion parameters were calculated, and the joint angles were efficiently interpolated by trigonometric-polynomial functions. The trajectories of the joint angles followed the earlier results of medical studies. Also, the gait features based on the motion parameters were extracted, and the *k*-NN classifier was used to analyze the discriminatory ability of the extracted features. The results produced classification rates of 97% CCR for 30 subjects and 84% CCR for 100 subjects. As such, the automated markerless analysis system not only accords with biomechanical analysis in the results it can produce, but also confirms recognition capability, as earlier suggested in biomechanical studies, and by computer vision-based approaches. There is interest in markerless gait analysis for medical purposes as its convenience will also benefit analysis of children and elderly. Further, there is opportunity for greater realism in biometrics and capacity to relate measures here to those of direct interest in clinical studies. We will doubtless require more sophisticated modeling strategies and perhaps with consideration of 3D geometry. This awaits further development, but the success of this necessary and initial approach and its ability to generate informative measurements in natural and non-invasive scenario encourage future developments.

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