MARKERLESS HUMAN GAIT ANALYSIS VIA IMAGE SEQUENCES

Jang-Hee Yoo and Mark S. Nixon
Department of Electronics and Computer Science,
University of Southampton, Southampton SO17 1BJ, UK
[jhy00r|msn]@ecs.soton.ac.uk

INTRODUCTION

The studies of human body motion have been motivated by a large number of application domains: visual surveillance, clinical analysis, computer animation, athletic performance analysis, robotics, and biometrics. Moreover, human motion analysis has many challenging issues, because the highly flexible structure and self-occlusion of the human body mandates complicated processes for the segmentation and analysis of motion (Leung, 1995). The motion of the human body may be defined by the movement of various body parts such as hand or limb segments. The human body consists of several rigid parts connected by the joints, but the motion of a full human-body is non-rigid and articulated (Aggarwal, 1998). Human gait (walking and running) is known to be one of the most universal and complex of all human activities. The human gait is a pattern of locomotion in which the body moves step by step in the desired direction, and it can be decomposed into periodic components within a gait cycle. Also, the human gait is usually described by kinetic or kinematic characteristics, and the pattern of rotation angles around the joints has been modelled as a pendulum (Murray, 1964; Taga, 1995), the motion of which is characterised by simple harmonic motion (Yam, 2002).

In addition, each person appears to have his or her own characteristic gait pattern. There is much evidence from psychophysical experiments (Johansson, 1973; Stevenage, 1999) and gait analysis (Inman, 1981; Murray, 1964; Winter, 1991) that gait patterns have characteristics of uniqueness for each individual. In computer vision, recognition of humans by gait has recently been become a challenging area (Nixon, 1999; Phillips, 2002). As a biometric, human gait may be defined as a means of identifying individuals by the way they walk (Nixon, 1999). Using gait has many advantages over other biometrics such as fingerprints, most notably that it is non-invasive and available at low resolution. On the other hand, human motion capture is crucial in computer graphics, clinical application and human identification. Many motion capture systems in computer vision (Moeslund, 2001) have been studied for tracking and extracting objects, though not for recognition purposes. In medical or biomechanical examination, most gait capture systems use external markers which represent the observed movement in the form of 3D trajectories that translate into kinematic variables such as body movements and joint angles (Kleissen, 1998). Marker based systems can acquire precise motion information, but require specialised hardware and subject contact. Therefore, markerless systems are essential to enable greater application capability.

In this paper, we propose a new markerless system for analysing and classifying human gait by computer vision techniques. The large amount of human gait data was collected from DV (digital video) cameras, and the human body and its contour is extracted from the image sequences. The human gait cycle is detected by analysing gait symmetry points and used for finding important gait phases. To extract the gait motion, body angles of each segment are extracted from gait skeleton data by linear regression analysis, and gait motion between key-frames is described by tracking the moving points of locomotion. Here, body segments and moving points are guided by topological analysis with anatomical knowledge, and a 2D stick figure is used to represent the human body model. Also, trajectory-based kinematic features are calculated from gait sequences for analysing the gait motion. Then, an enhanced back-propagation algorithm is employed to classify the gait features. As such, the new system aims to derive measures of biomechanical significance, in part demonstrated by recognition capability.

METHODS

In computer vision, motion analysis of the human body usually involves segmenting, tracking and recovering the human body motion in an image sequence. The markerless gait analysis system consists of four stages: *i*) extraction of moving human body and its contour from image sequences, *ii*) detection of the gait cycle by symmetry analysis, *iii*) extraction of gait figure by the joint angles and body points, and *iv*) kinematic analysis and feature extraction for classifying the gait patterns. Fig. 1 shows the system architecture used within this study.

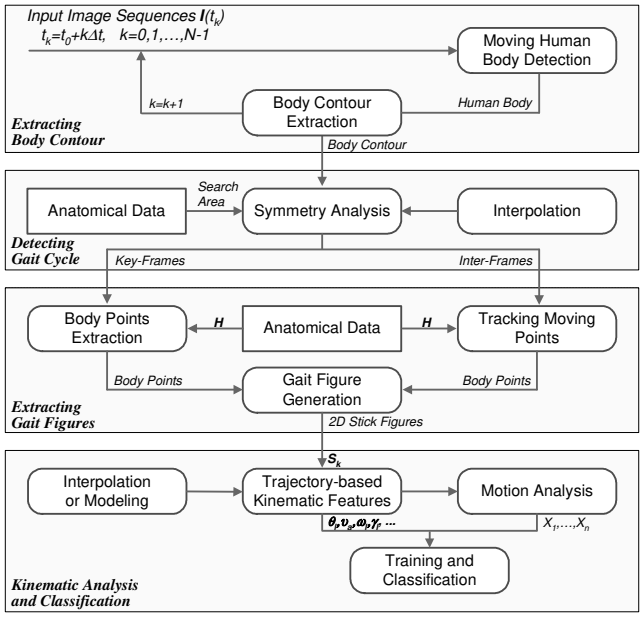


Figure 1: Overview of the Proposed System

Extracting Human Body Contour

Our database (Shutler, 2002) comprises two forms of indoor data (under controlled lighting with special background) and one outdoors (without lighting or background control) data. The first form of indoor data is of a subject walking on a treadmill, and the second form is of a subject walking alone

a specially designed continuous track. Sample images from the database are shown in Fig. 2. As can be seen in Fig. 2(a), a chroma-key laboratory was constructed to allow controlled lighting conditions for the indoor treadmill and track data. An image sequence contains a single subject walking at normal speed and was acquired at 25 frames / second with 720×576 colour pixels from a DV camera. Also, the subject was filmed walking in both directions, and the database contains more than 100 subjects. Accordingly, a markerless analysis system can contribute to the debate concerning the use of a treadmill versus normal walking, for a large number of subjects.

(a) Indoor Data (b) Outdoor Data

Figure 2: Images from the Database

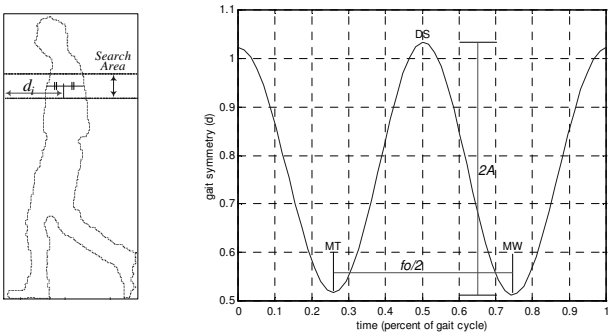
In the indoor data, human body extraction from the image sequences is easily achieved through background subtraction. After that, the histogram projection profiles are analysed to estimate the position of a human body, and the body region is verified by prior knowledge such as size and shape. Thresholding and morphology is then used to extract the contour of a detected human body. Here, a thresholding method based on similarity measures between the background and the object image is used (Yoo, 2002). Finally, the body contour is extracted by 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.

Detecting Human Gait Cycle

During walking, the human body functionally divides into the passenger and locomotor units (Perry, 1992). The upper body is a relatively passive passenger unit that rides on a locomotor unit. The two lower limbs and pelvis are the anatomical segments that form the locomotor unit. The passenger unit must be balanced on a joint that is in space, therefore, it is moving in the plan of progression as an inverted pendulum rotates about the hip joint (Winter, 1991). Namely, the centre of mass of the passenger unit will keep the maximum distance from front foot at the double supports, and it has minimum distance from the front foot at mid-stance (MT) or mid-swing (MW). Fig. 3(a) shows a horizontal centre of mass at chest region which is guided by anatomical data. To detect the gait cycle, the horizontal centre of mass in the passenger unit is considered as a gait symmetry point. This gait symmetry point can be defined as

$$s_i = d_i / (\bar{d} + \sigma) \qquad (1)$$

where $\bar{d}$ is mean value and σ is standard derivation of d_i during one gait cycle. Fig. 3(b) shows the curves of gait symmetry interpolated by Eqn. 2 during a gait cycle. Important gait phases (three double supports and two single supports) can be detected by the obvious peak points (three maxima and two minima). Some gait features such as gait frequency (f_0), amplitude (A), and walking velocity (v) can be also calculated.



(a) CoM (b) Gait Symmetry Analysis

Figure 3: Detecting Gait Cycle

Human gait is a form of periodic motion, especially when walking laterally; hence we can predict human movement in a gait cycle. Statistical analyses of the gait relationships typically use continuous curves of the time series data measured over the gait cycle. Murray (1964) considered 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 (Murray, 1964; Taga, 1995). 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 (Yoo, 2002). Also, further gait motion can be predicted by the periodicity of this interpolation model. An n^{th}-order trigonometric polynomial interpolant function is

$$y_n(x) = a_0 + a_n \cos(2\pi n x) + \sum_{k=1}^{n-1} [a_k \cos(2\pi k x) + b_k \sin(2\pi k x)] \qquad (2)$$

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

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 were extensively studied (Dempster, 1967; Drillis, 1966). To extract body points in a contour image, a skeleton data with body segment properties is used. For a body height H, an initial estimate of the vertical position of the neck, shoulder, waist, pelvis, knee and ankle was set by 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 calculated by two border points of each body part p with a range constraint as

$$x_{s,p} = (x_{b,p} + x_{e,p})/2 \qquad (3)$$

where x_b and x_e represent the horizontal position of the begin and the end pixels on the horizontal line respectively. For example, the range constraint for trunk t can be given by

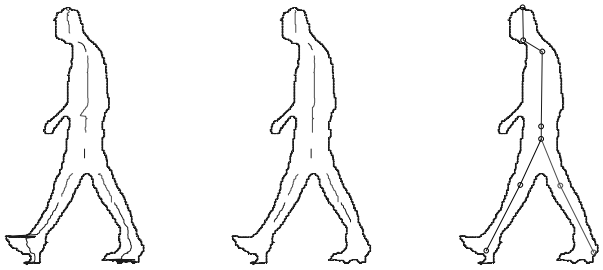
mean value of neck's border points (or not labelled, ∅) as

$$x_{s,t} = \begin{cases} x_{s,t} & if\ \ (\overline{x}_{b,neck} < x_{s,t} < \overline{x}_{e,neck}) \\ \varnothing & otherwise \end{cases}. \quad (4)$$

In images, estimation of a primary gait skeleton is highly susceptible to difficulty by the movement of the arm and foot. Therefore, a noise removal method, using mean value and standard derivation in each body part, is employed to select a skeleton point as

$$x'_{s,p} = \begin{cases} x_{s,p} & if\ \ \left(x_{s,p} \subset \overline{x} \pm (\sigma + \alpha \cdot \sigma')\right) \\ \varnothing & otherwise \end{cases} \quad (5)$$

where σ' is standard derivation of $x'_{s,p}$ and α is parameter ($1 \le \alpha \le 2$) which depends on the body part. Figs. 4(a) and (b) show the gait skeleton and the noise removed skeleton data.



(a) Skeleton (b) Sampling (c) Stick Figure

Figure 4: Extracting Body Points at Key-frame

Now we can calculate the body angles from the skeleton data by using linear regression. The angles θ_p of body part p can be approximated by using the slope of the lines in linear regression equation as

$$\theta_p = \tan^{-1}\left(\sum_{i=1}^{n}(x_i - \overline{x})^2 \Big/ \sum_{i=1}^{n}(y_i - \overline{y})(x_i - \overline{x})\right) \quad (6)$$

where n is the number of the skeleton points. Each body point (position) can be calculated by

$$x_p, y_p = \left[x_i + L_p \cos(\phi + \theta_p) \quad y_i + L_p \sin(\phi - \theta_p)\right] \quad (7)$$

where ϕ is the phase shift, x_i and y_i are the coordinates of a previously established position, and L_p is the length of body segments guided by anatomical knowledge (Dempster, 1967; Drillis, 1966). As shown in Fig. 4(c), a 2D stick figure with the nine body points is derived from the skeleton data of each body segment by linear regression.

On the other hand, the body points are clearly extracted around three double support phases (initial contact, terminal stance, and terminal swing), but the points around single support phases are not as good as 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 left-most skeleton points around the knee region and the right-most skeleton points around the ankle region are considered. Namely, the skeleton points by a size of each body segment are sorted as

$$\boldsymbol{x}_{knee} = \{x \mid x_i < x_{i+1}\} \ \ and \ \ \boldsymbol{x}_{ankle} = \{x \mid x_i > x_{i+1}\}. \quad (8)$$

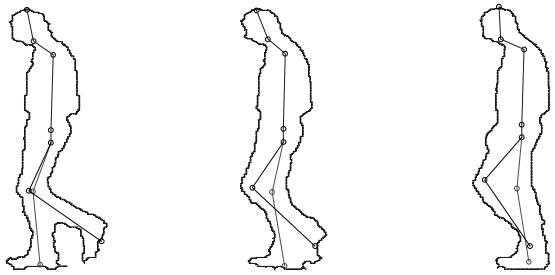
The proper size of body segments is also guided by anatomical knowledge. The knee and ankle points for tracking are given by mean value of sorted data as

$$\boldsymbol{x}_s = \{x_i \mid i = m,...,n\} \ \ and \ \ \overline{x}_s = mean(\boldsymbol{x}_s) \quad (9)$$

where m and n are sequence index of sorted data, here set to *3* and *5* respectively. The forward displacement Δx_t at frame t is calculated as

$$\Delta x_t = \overline{x}_t - \overline{x}_{t-1}. \quad (10)$$

Finally, the body points at frame t are computed by Eqns. 6 and 7 using the new angle values and segment sizes of thigh and shin.



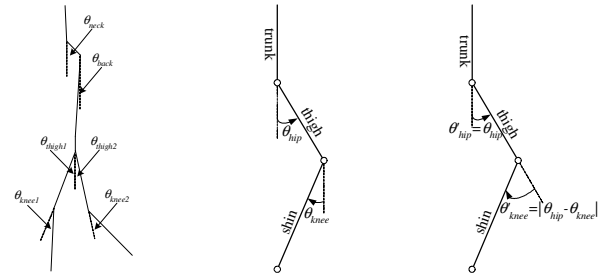
(a) t-1 (b) t (MT/MW) (c) t+1

Figure 5: Body Points at Crossover of the Legs

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 lower than hip angles. The crossover of the two legs is performed on two single support points during one gait cycle. Fig. 5 shows an example of the body point extraction by using the gait constraints. In the figure, the crossover of knee is detected during the three frames of a single support, and ankle crossover is started after a single support. These constraints of human walking are used to improve the robustness of the method.

Kinematic Feature Extraction

There are nine coordinates (body points) extracted by linear regression of skeleton data and motion tracking with topological analysis. The 2D stick figure is obtained by connecting the nine coordinates. The definition of joint angles in the stick figure is shown in Fig. 6(a). By definition (Winter, 1991), the joint angles are relative, thus the relative angles in each joint were computed from the measured values of the angles. The definition of measurement angles and relative joint angles is shown in Figs. 6(b) and (c). In normal walking, the trunk of human body can be considered to be almost vertical, and the relative knee angles can be calculated by the measurement hip and knee angles.



(a) Joint Angles (b) Measured Angles (c) Relative Angle

Figure 6: Gait Figures and Joint Angles

Also, the mean and variation of the gait angles for single sequence of each subject are extracted as features. The variation of the gait angles can be obtained by standard derivation during one gait cycle. Trajectories of gait figure 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_t at frame t is calculated by

$$v_t = (x_t - x_{t-1})/\Delta t. \quad (11)$$

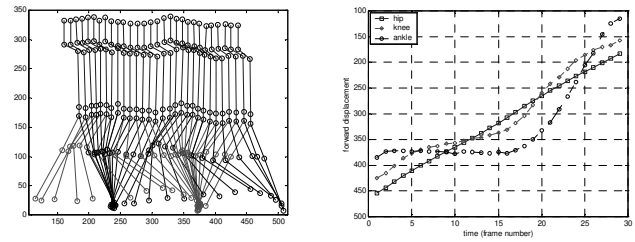
The angular velocities ω_t at frame t, given an inter-frame time Δt (1/25 sec), are

$$\omega_t = (\theta_t - \theta_{t-1}) \ / \ \Delta t. \quad (12)$$

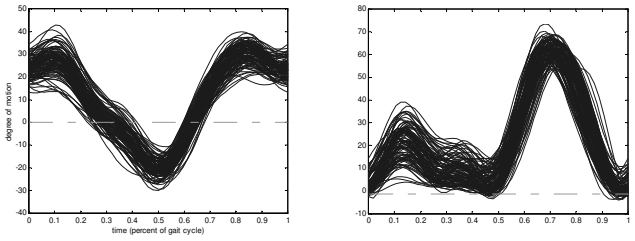
The trajectories are basically vector-valued function at each frame t of an image sequence, and they are periodic as in gait motion.

RESULTS AND DISCUSSIONS

In the experiments, seven indoor image sequences of each of the 100 subjects are used. A set of gait data extracted from image sequences provides potentially valuable time-dependent pattern as a gait time series. The extracted gait figures from an image sequence during one gait cycle shown in Fig. 7(a), and its forward displacement at hip, knee, and ankle shown in Fig. 7(b). The forward displacement of joints is consistent with medical data by Inman's (1981) analysis, and it is an important component for showing quality of the data. Also, human gait motion can be described in a compact form, as a sequence of the joint parameters. Figs. 7(c) and (d) show the time series data of 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. As in the medical studies (Murray, 1964; Perry, 1992), the hip and knee at initial contact are flexed about 20°~30° and 0°~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.



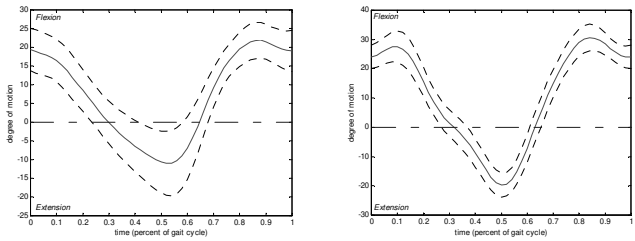
(a) Sequence of Gait Figures (b) Forward Displacement



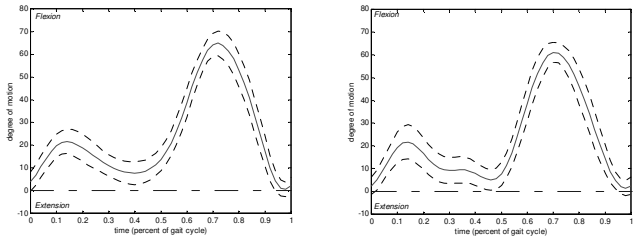
(c) Hip Angles vs. Time (d) Knee Angles vs. Time

Figure 7: Gait Motion during One Gait Cycle

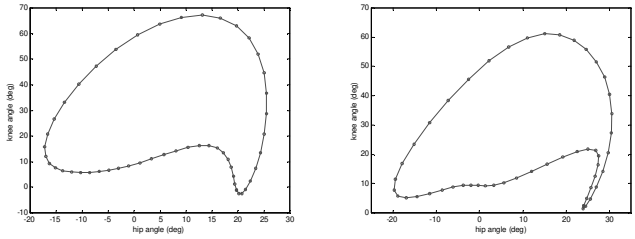
Figs. 8(a) and (c) show the mean and standard derivation, by biomechanical data from anatomical markers in limb segments (Winter, 1991), for joint angles of the hip and knee motion during one gait cycle, and Figs. 8(b) and (d) show the results of measuring relative joint angles during a gait cycle. The results show that the new approach works successfully, comparing well with biomechanical data acquired by a marker-based system. The variance here would appear to be smaller than for Winter's (1991) analysis. These results concern 100 subjects with seven sequences of each subject, a total of 700 sequences (≅19,534 images), i.e. a much larger volume of data than in that 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 revised by this new approach.



(a) Hip Angles (Winter) (b) Hip Angles (Measured)



(c) Knee Angles (Winter) (d) Knee Angles (Measured)

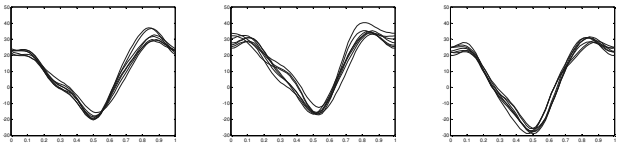


(e) Cyclogram (Winter) (f) Cyclogram (Measured)

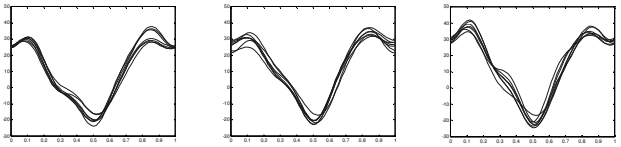
Figure 8: Gait Angles during One Gait Cycle

Also, a cyclogram (Goswami, 1998) is demonstrated by ignoring the time axis of each curve and directly plotting knee angle versus hip angle as shown in Figs. 8(e) and (f). In the figures, the graphs show that very similar result between measured and Winter's analysis. The cyclogram provides information about the posture of the leg and the coordination of two joints but no information about the velocities involved. However, the hip-knee cyclogram is an important signature of human gait motion, and the periodicity is reflected in closure of the two-dimensional figure. As such, using angle versus angle plots rather than angle versus time curves improves understanding of gait. The main reason for this is the fact that the shape of the loops is easily recognisable, especially by eye.

One the other hand, one of the most distinctive characteristics of human gait is the fact that it is individualistic. As can be seen in Fig. 9, each person has little difference between the curves from seven different image sequences, and the shapes of the basic curves differ between subjects.



(a) subject #1 (b) subject #2 (c) subject #3



(d) subject #4 (e) subject #5 (f) subject #6

Figure 9: Gait Motion of Each Subject with 7 Sequences

To identify humans by their gait, an enhanced back-propagation neural network algorithm is employed as a classifier. We have mainly used the 20 features extracted based on kinematic analysis during one gait cycle. In training phase, the classification rate was 86% for three sequences (95% for two sequences) of 100 subjects, but we could not reach meaningful performance for recognition. However, the recognition rate for a small number (10) of subjects was 100%. Naturally we seek to extend the technique in terms of biometric application capability as well as analysing a large number of subjects in future. Notwithstanding this, the markerless approach can clearly handle a small number of subjects successfully. By this, these measurements show that people are unique by their walking pattern, according with earlier biomechanical suggestions, and buttressing other similar results.

CONCLUSIONS

We have described an automated markerless gait analysis system using computer vision techniques. The gait cycle was detected by symmetry property of the horizontal centre of mass. The gait figure was extracted from the body contour by determining the body points using linear regression and motion tracking with topological analysis. The joint angles extracted from a sequence of the gait figures were interpolated by trigonometric-polynomial functions. Also, trajectory-based kinematic features were extracted, and the enhanced back-propagation algorithm was employed for classifying the gait. As such, anatomical knowledge has guided development of a markerless gait analysis system that not only accords with biomechanical analysis in the results it can produce, but also confirms uniqueness - as earlier suggested in biomechanical studies. In future, we require a more features of gait motion for describing and recognising the gait activities, and a more sophisticated classification algorithm.

ACKNOWLEDGEMENTS

We gratefully acknowledge partial support by the European Research Office of the US Army under Contract No. N68171-01-C-9002.

REFERENCES

Aggarwal, J. K., et al (1998). Nonrigid Motion Analysis: Articulated and Elastic Motion. *Computer Vision and Image Understanding*, **70**(2), pp.142-156.

Dempster, W. T. and Gaughran, G. R. L. (1967). Properties of Body Segments Based on Size and Weight. *American Journal of Anatomy*, **120**, pp.33-54.

Drillis, R. and Contini, R. (1966). *Body Segment Parameters*. TR 1163-03, New York University, Under Contract with Office of Vocational Rehabilitation, Department Health, Education and Welfare, New York.

Goswami, A. (1998). A New Gait Parameterization Technique by Means of Cyclogram Moments: Application to Human Slop Walking. *Gait and Posture*, **8**(1), pp.15-36.

Inman, V. T., Ralston, H. J. and Todd, F. (1981). *Human Walking*, Williams & Wilkins.

Johansson, G. (1973). Visual Perception of Biological Motion and a Model for Its Analysis. *Perception and Psychophysics*, **14**(2), pp.201-211.

Kleissen, R. F. M., et al (1988). Electromyography in the Biomechanical Analysis of Human Movement and its Clinical Application. *Gait and Posture*, **8**(2), pp.143-158.

Leung, M. K. and Yang, Y. H. (1995). First Sight: A Human Body Outline Labeling System. *IEEE Transactions on PAMI,* **17**(4), pp.359-377.

Moeslund, T. B. and Granum, E. (2001). A Survey of Computer Vision-based Human Motion Capture. *Computer Vision and Image Understanding*, **81**(3), pp.231-268.

Murray, M. P., Drought, A. B. and Kory, R. C. (1964). Walking Patterns of Normal Men. *Journal of Bone and Joint Surgery*, **46A**(2), pp.335-360.

Nixon, M. S. et al (1999). Automatic Gait Recognition. in *BIOMETRICS - Personal Identification in Networked Society*, A. K. Jain, et al. Eds., pp.231-249, Kluwer Academic.

Perry, J. (1992). *Gait Analysis: Normal and Pathological Function*, Slack.

Phillips, P. J. (2002). Human Identification Technical Challenges. *Proceedings of ICIP 2002*, pp.49-52.

Shutler, J. D., et al (2002). On a Large Sequence-based Human Gait Database. *Proceedings of RASC 2002*, pp.66-71.

Stevenage, S. V., Nixon, M. S. and Vince K. (1999). Visual Analysis of Gait as a Cue to Identity. *Applied Cognitive Psychology*, **13**, pp.513-526.

Taga, G. (1995). A Model of the Neuro-Musculo-Skeletal System for Human Locomotion. *Biological Cybernetics*, **73**(2), pp.97-111.

Winter, D. A. (1991). *The Biomechanics and Motor Control of Human Gait: Normal, Elderly and Pathological*, 2nd Eds., Waterloo Biomechanics.

Yam, C. Y., et al (2002). On the Relationship of Human Walking and Running: Automatic Person Identification by Gait. *Proceedings of ICPR 2002*, pp.287-290.

Yoo, J. H., Nixon, M. S. and Harris, C. J. (2002). Model-Driven Statistical Analysis of Human Gait Motion. *Proceedings of ICIP 2002*, pp.285-288.