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On Laboratory Gait Analysis via Computer Vision

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Abstract

We describe a marker-less system for analysing and classifying human gait motion by combining a statistical approach and motion tracking with topological analysis guided by anatomical knowledge. The marker-less gait analysis system consists of three stages: detection and extraction of the moving human body and its contour from image sequences; extraction of human gait motion by the joint angles and body points; and kinematic analysis and feature extraction for classifying the gait pattern. The periodic motion of human gait is described by symmetry, and a 2D stick figure is used to represent the human gait model. The usefulness of proposed method is demonstrated in marker-less gait analysis with comparison to biomechanical data.

1 Introduction

The ability to recognise humans and their activities by computer vision is a very important task, with many potential applications (Gavrila 1999). Human gait (walking and running) is known to be one of the most universal and complex of all human activities, and each person appears to have his or her own characteristic gait pattern (Inman 1981, Murray 1964, Winter 1991). 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. However, 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, marker-less systems are essential to enable greater application capability.

In this paper, we propose a new marker-less 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. 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.

2 Describing Human Gait Motion

2.1 Human Gait Database

Early gait databases reported in the literature were collected under very limited conditions and consisted of a relatively small number of subjects. To overcome this, larger databases have recently been developed by DARPA Human ID projects (Phillips 2002). The SOTON database (Shutler 2002) developed by the ISIS Research Group is one of the recent databases in the DARPA project. The SOTON database comprises two forms of indoor data (under controlled lighting with special background) and one outdoors (without lighting or background control). The first form of indoor data is a subject walking on a treadmill, and the second form is subject walking alone a specially designed continuous track.

(a) Indoor Data

(b) Outdoor Data

Figure 1: Images from SOTON Database

Sample images from the database are shown in Fig. 1. As can be seen in Fig. 1(a), chroma-key laboratory was constructed to allow controlled lighting conditions for the indoor treadmill and track data. An image sequence contains only 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 marker-less analysis system can contribute to the debate concerning the use of a treadmill versus normal walking, for a large number of subjects.

In addition, 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.

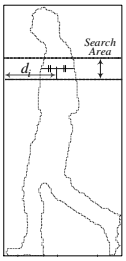
2.2 Detecting Human Gait Cycle

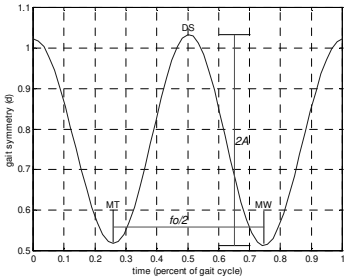
During walking, the human body functionally divides into the passenger and locomotor units. The upper body is a relatively passive passenger unit that rides on a locomotor unit. The two lower limbs and pelvis are the anatomical segments that form the locomotor unit. Each gait cycle is separated into two distinct periods: the stance and the swing phases (Perry 1992). 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). In general, the stance and swing phases have been divided into eight sub-phases: initial contact, loading response, mid-stance, terminal stance, pre-swing, initial swing, mid-swing, and terminal swing.

On the other hand, 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. 2(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 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. 2(b) shows the curves of gait symmetry interpolated by trigonometric-polynomials (Yoo 2002) during a gait cycle. Important gait phases (three double supports and two single supports) can be detected by the obvious peak points (three maximum and two minimum). Some gait features such as gait frequency (f_0), amplitude (A), and walking velocity (v) can be also calculated by this analysis.





(a) CoM (b) Gait Symmetry Analysis

Figure 2: 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. Murray (1964) considered human gait as "a total walking cycle" - the action of walking can be thought of as a periodic signal. Accordingly, the pattern of rotation angles around the joints has been modelled as a pendulum, the motion of which is characterised by simple harmonic motion. This assumes that the pattern of the motion is approximately sinusoidal in nature (Cunado 1997, Taga 1995). The sinusoidal functions are basically all periodic. Therefore, gait motion can be characterised as having a periodic component.

3 Extracting Human Gait Motion

3.1 Body Points Extraction

To extract body points in a contour image, a skeleton data with body segment properties is used. For a body height H, the vertical position of the neck, shoulder, waist, pelvis, knee and ankle was set by study of anatomical data (Dempster 1967, Winter 1990) 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

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

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 as

$$x_{s,t} = \begin{cases} x_{s,t} & if\ \ (\overline{x}_{b,neck} < x_{s,t} < \overline{x}_{e,neck}) \\ \varnothing & otherwise \end{cases}. \tag{3}$$

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

$$x'_{s,p} = \begin{cases} x_{s,p} & if\ \ \left(x_{s,p} \subset \overline{x} \pm (\sigma + \alpha \cdot \sigma')\right) \\ \varnothing & otherwise \end{cases} \tag{4}$$

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. 3(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 using linear regression analysis. The angles θ_p of body part p can be approximated by using the slope of the lines in linear regression equation as

$$\theta_p = \tan^{-1}\left(\sum_{i=1}^{n} (x_i - \overline{x})^2 \Big/ \sum_{i=1}^{n} (y_i - \overline{y})(x_i - \overline{x}) \right) \tag{5}$$

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

$$x_p, y_p = \left[x_i + L_p \cos(\phi + \theta_p) \quad y_i + L_p \sin(\phi - \theta_p) \right] \tag{6}$$

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). As shown in Fig. 3(c), a 2D stick figure with the nine body points is derived from the skeleton data of each body segment by linear regression.

3.2 Tracking Moving Points

In section 2.2, the important gait phases are detected by gait cycle analysis. 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 low limbs. To track knees and ankles, the left-most skeleton points around knee region and the right-most skeleton points around ankle region are considered. Namely, the skeleton points by a size of each body segment are sorted as

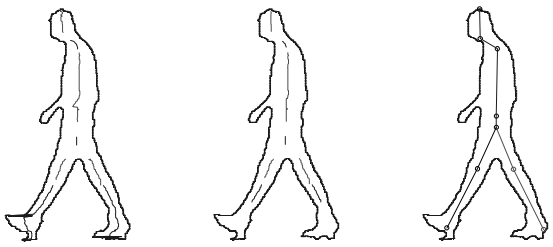
$$\boldsymbol{x}_{knee} = \{x \mid x_i < x_{i+1}\} \ \ and \ \ \boldsymbol{x}_{ankle} = \{x \mid x_i > x_{i+1}\}. \tag{7}$$

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

$$\boldsymbol{x}_s = \{x_i \mid i = m, ..., n\} \ \ and \ \ \overline{x}_s = mean(\boldsymbol{x}_s) \tag{8}$$

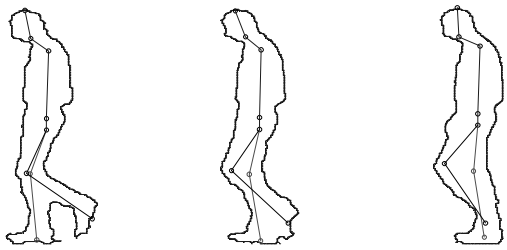
where m and n are sequence index of sorted data, here set to 3 and 5 respectively. The forward displacement Δx_t at frame t is calculated as

$$\Delta x_t = \overline{x}_t - \overline{x}_{t-1}. \tag{9}$$



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

Figure 3: Extracting Body Points at Key-frame



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

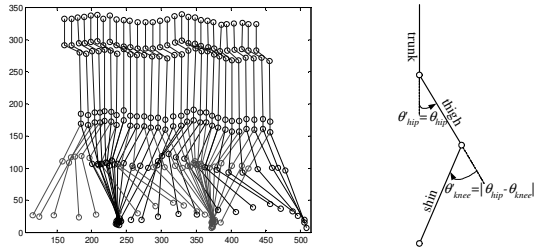
Figure 4: Body Points at Crossover of the Legs

Finally, the body points at frame t are computed by Eqns. (5) and (6) 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 lower than hip angles. The crossover of the two legs is performed on two single support points during one gait cycle. Fig. 4 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.

3.3 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 obtained by connecting the nine coordinates. Fig. 5(a) shows the extracted stick figures during one gait cycle. We can re-calculate the six angles which are associated with joint positions: θ_{neck}, θ_{back}, θ_{thigh1}, θ_{thigh2}, θ_{knee1}, and θ_{knee2}. 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 relative joint angles is shown in Fig. 5(b).



(a) Sequence of Gait Figures (b) Relative Angle

Figure 5: Gait Figures and Joint Angles

On the other hand, 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

$$v_t = (x_t - x_{t-1})/\Delta t. \quad (10)$$

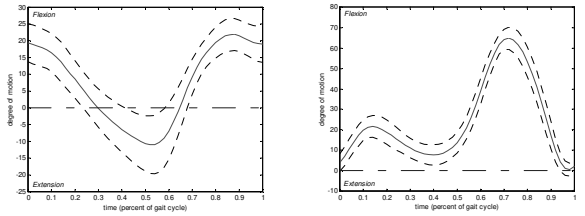
Also, the angular velocities ω_t at frame t, given an inter-frame time Δt (1/25 sec), are

$$\omega_t = (\theta_t - \theta_{t-1}) \ / \ \Delta t. \quad (11)$$

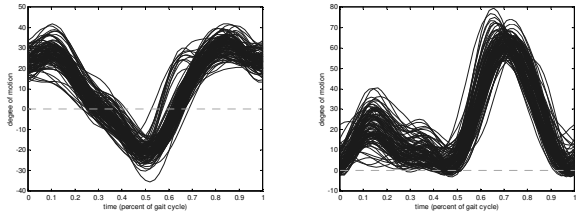
The trajectories are basically vector-valued function at each frame t of an image sequence, and they are periodic as in gait motion.

4 Results

In the experiments, three 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. Figs. 6(a) and (b) show the mean and standard derivation, by biomechanical data from anatomical markers in limb segment (Winter 1991), for joint angles of the hip and knee motion during one gait cycle, and Figs. 6(c) and (d) show the results of measuring relative joint angles during a gait cycle. In the figures, the lines are the curves that result from using 4th-order trigonometric-polynomial interpolants.



(a) Hip Angles (Winter) (b) Knee Angles (Winter)



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

Figure 6: Gait Motion during One 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 larger than for Winter's (1991) analysis. These results concern 100 subjects, 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

should be revised by this new approach.

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 82% for three sequences (93% 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 marker-less 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.

5 Conclusions

We have described an automated marker-less 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 body contour by determining the body points using the linear regression of body skeleton 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 marker-less 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

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References

D. Cunado, M. S. Nixon, and J. N. Carter. Using Gait as a Biometric, via Phase-Weighted Magnitude Spectra. in *Proceedings of the 1st International Conference on Audio-and Video-based Biometric Person Authentication*, pp.95-102, Crans-Montana, Switzerland, March 1997.

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

D. M. Gavrila. The Visual Analysis of Human Movement: A Survey. *Computer Vision and Image Understanding*, **73**(1), pp.82-98, January 1999.

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

R. F. M. Kleissen, J. H. Buurke, J. Harlaar, and G. Zilvold. Electromyography in the Biomechanical Analysis of Human Movement and its Clinical Application. *Gait and Posture*, **8**(2), pp.143-158, 1998.

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

M. S. Nixon, J. N. Carter, D. Cunado, P. S. Huang, and S. V. Stevenage. Automatic Gait Recognition. in *BIOMETRICS - Personal Identification in Networked Society*, A. K. Jain, et al. Eds., pp.231-249, Kluwer Academic, 1999.

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

P. J. Phillips. Human Identification Technical Challenges. in *Proceedings of the IEEE 2002 International Conference on Image Processing*, pp.49-52, Rochester, USA, September 2002.

J. D. Shutler, M. G. Grant, M. S. Nixon, and J. N. Cater. On a Large Sequence-based Human Gait Database. in *Proceedings of Recent Advances in Soft Computing*, pp.66-71, Nottingham, UK, December 2002.

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

D. A. Winter. *The Biomechanics and Motor Control of Human Movement*, 2nd Eds., John Wiley & Sons, 1990.

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

J. H. Yoo, M. S. Nixon and C. J. Harris. Model-Driven Statistical Analysis of Human Gait Motion. in *Proceedings of the IEEE 2002 International Conference on Image Processing*, pp.285-288, Rochester, USA, September 2002.