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Gait Recognition by Walking and Running: A Model-Based Approach

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Abstract

Gait is an emerging biometric for which some techniques, mainly holistic, have been developed to recognise people by their walking patterns. However, the possibility of recognising people by the way they run remains largely unexplored. The new analytical model presented in this paper is based on the biomechanics of walking and running, and will serve as the foundation of an automatic person recognition system that is invariant to these distinct gaits. A bilateral and dynamically coupled oscillator is the key concept underlying this work. Analysis shows that this new model can be used to automatically describe walking and running subjects without parameter selection. Temporal template matching that takes into account the whole sequence of a gait cycle is applied to extract the angles of thigh and lower leg rotation. The phase-weighted magnitudes of the lower order Fourier components of these rotations form the gait signature. Classification of walking and running subjects is performed using the k-nearest-neighbour classifier. Recognition rates are similar to that achieved by other techniques with a similarly sized database. Future work will investigate feature set selection to improve the recognition rate and will determine the invariance attributes, for inter- and intra- class, of both walking and running.

1. Introduction

Dating back to the 5th century B.C., the study of human locomotion as well as individual variation during running and sprinting were reflected in ancient Greek art. Later, Shakespeare observed that we could recognise acquaintances by the way they walk. These observations suggest that people could be recognised not only by the way they walk, but also by the way they run. Aristotle described different types of animal gaits as well as human gait. He observed that human gait when walking, is symmetrical and when one walks, the body moves in an undulating manner. These observations inspired the development of this new model.

Biometrics play an important role in individual authentication and recognition in today's society. Gait is a newly emergent biometric for which some techniques, mainly holistic, have been developed to recognise people by the way they walk. However, the possibility of recognising people by the way they run remains largely unexplored. Criminals not only walk naturally to escape, very often they run! Hence, a more robust gait recognition system which can handle both running and walking is essential. Our secondary objective is to promise that it might be possible to determine invariance relationships between walking and running, to improve application capability.

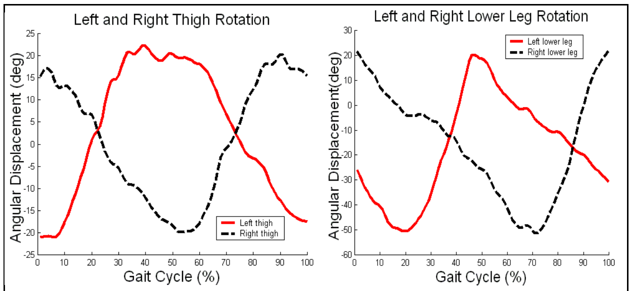
Perhaps the earliest approach to gait recognition was to derive a gait signature from a spatio-temporal pattern[1]. Another approach was to project the images into eigenspace and the resulting eigenvectors were used for recognition[2]. Then, dense optical flow[3] was used to determine the relative phases of optical flow to form a feature vector to create a signature. A more recent statistical based approach combined canonical space transformation based on linear discriminant analysis with the eigenspace transformation which later incorporated the temporal information obtained from the optical-flow changes between two consecutive images to improve recognition capability[4]. Eigen analysis has also been applied to similarity metrics[5], again achieving encouraging recognition rates. Then, Shutler developed a technique that makes use of velocity moments, an extended form of centralised moments which have the ability to describe an object and its motion[6]. A recent approach for visual discrimination of children from adults in video, uses characteristic regularities present in their locomotion patterns[7]. Johnson demonstrated that gait recognition can also be achieved by using recovered static body parameters[8] of subjects.

The earliest model-based human gait recognition system models human walking as a pendulum representing the thigh motion, which combined a velocity Hough transform with a Fourier representation to obtain a gait signature[9]. Recently, a model-based gait recognition system, which includes the motion model of the thigh and lower leg rotation that describes both walking and running, provides promising recognition rates[10]. Nevertheless, this model lacks analytical precepts and is rather heuristic in nature. Here, we do not attempt to describe gait with a precise biomechanical model due to its high complexity. However, based on knowledge of the biomechanics of walking and running, we describe a new model that is invariant to these two distinct gaits, which appears sufficient to serve as the foundation of an automatic gait recognition system. This technique produces similar recognition results to those we achieved earlier[10] but without the need of parameter selection, i.e. a totally automatic manner. As such, this new model is better suited for a fully automatic gait recognition system which is invariant to walking and running.

2. Gait Modelling and Analysis

An understanding of the underlying mechanism of gaits is essential in order to develop a model well suited describing the motion. In terms of biomechanical definition, walking and running are distinguished firstly by the stride duration, stride length, velocities and the range of motion made by the limbs. The kinematics of running differs from walking in a way that the joints' motion increases significantly as the velocity increases. Secondly, by whether there exist periods of *double support* or *double float*. The most distinct difference between walking and running is that for walking there exists a period where both feet are in contact with the ground (*double support*), whereas for running, there exists a period where both feet are not in contact with the ground (*double float*).

2.1 Pattern of Movement



(a) (b)

Fig. 1: Thigh and lower leg rotation of the left and right leg with half a period phase shift.

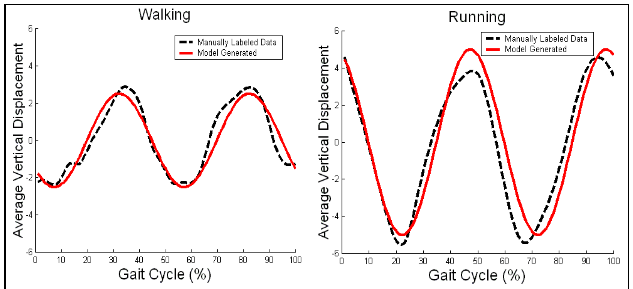
Human locomotion is naturally rhythmic producing a co-ordinated oscillatory behaviour. One of the unique characteristics of walking and running is bilateral symmetry, that is, when one walks or runs, the left arm and right leg interchange their direction of swing with the right arm and left leg, and vice versa, with half a period phase shift. **Fig 1** shows the manually labelled thigh and lower leg rotation of the left and right leg measured from the vertical. This shows that the motions of the left and right leg are coupled by half a period phase shift. Hence, only one model is needed to describe the motion of both legs.

2.2 The Analytical Motion Model: Dynamically Coupled Oscillator

2.2.1 Hip Motion. To ease data acquisition, the subjects are imaged walking and running on a motorised treadmill at constant velocities and because the horizontal position of the hip is known, the horizontal displacement of the hip is insignificant enough to be ignored. However, the vertical displacement of the hip is essential as it differs for walking and running. As depicted in **Fig. 2**, during running the amplitude of the displacement is bigger and has a relative phase shift with respect to the one for walking. This is described by S_y,

$$S_y(t) = A_y \sin(2\omega t + \phi_y) \quad \textbf{(1)}$$

where A_y is the amplitude of the vertical oscillation, ω is the fundamental frequency and ϕ_y is the relative phase shift. Since a gait cycle consists of two steps, the frequency is twice that of the leg motion that will be described in a later section. That is, every time we make a step, the body lowers and lifts, which gives the variations as shown in **Fig. 2**. Here, all the plots are normalised to a complete gait cycle so that they are invariant to speed. The superimposed graphs reflect the veracity of this simple model, by comparing the model generated vertical displacement of the hip with that of manually labelled data. The structure is clearly the same.



(a) (b)

Fig. 2: The relative vertical displacement of hip during walking and running.

2.2.2 Thigh and Lower Leg Motion. The human lower limb can be represented as two penduli joined in series, see **Fig. 3**. This new model solves the differential equations obtained from the dynamic model of these two penduli.

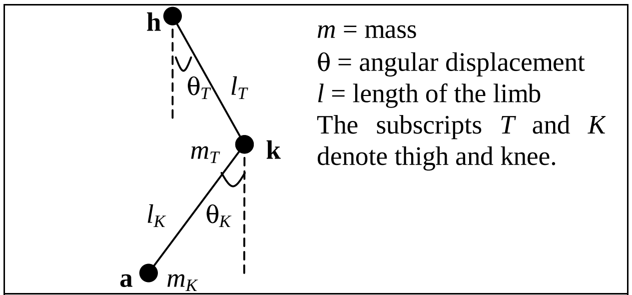


Fig. 3: The dynamically coupled pendulum model.

Let us consider the upper pendulum where the external force, $\mathbf{F}(t) = 0$, the motion equation is

$$\ddot{\theta}_T + \frac{\omega_T^2}{m_T}\theta_T = 0 \tag{2}$$

where θ_T is the angular displacement from the vertical, $\ddot{\theta}_T$ is the angular acceleration, m_T is the mass and ω_T is the natural frequency. Solving the ordinary differential equation (ODE) gives the basic motion model for thigh rotation, which is

$$\theta_T = A\cos\left(\frac{\omega_T}{\sqrt{m_T}}t\right) + B\sin\left(\frac{\omega_T}{\sqrt{m_T}}t\right) \tag{3}$$

where A and B are constants, and t is the time index which varies from 0 to 1.

In reality, the motion of the lower pendulum is a very complex process that is hard to model precisely. As we seek a model providing a basis for recognition, we shall assume that the lower leg can be modelled as a driven oscillator where the force applied to it is related to the motion of the upper pendulum. Following an analogy of Newton's laws, by differentiating **Eq.3** twice, we have

$$\ddot{\theta}_T = -\frac{\omega_T^2}{m_T}\left[A\cos\left(\frac{\omega_T}{\sqrt{m_T}}t\right) + B\sin\left(\frac{\omega_T}{\sqrt{m_T}}t\right)\right] \tag{4}$$

which contributes to the driving force to the lower pendulum. This force is given by

$$\mathbf{F}(t) = -\omega_T^2\left[A\cos\left(\frac{\omega_T}{\sqrt{m_T}}t\right) + B\sin\left(\frac{\omega_T}{\sqrt{m_T}}t\right)\right] \tag{5}$$

Similar to **Eq. 2**, the motion equation for the lower pendulum is

$$\ddot{\theta}_K + \frac{\omega_K^2}{m_K}\theta_K = -\frac{\mathbf{F}(t)}{m_K} \tag{6}$$

Substituting **Eq. 5** into **Eq. 6**, yields

$$\ddot{\theta}_K + \frac{\omega_K^2}{m_K}\theta_K = \frac{\omega_T^2}{m_K}\left[A\cos\left(\frac{\omega_T}{\sqrt{m_T}}t\right) + B\sin\left(\frac{\omega_T}{\sqrt{m_T}}t\right)\right] \tag{7}$$

The solution for θ_K will comprise the general solution, θ_{Kg}, and the particular solution, θ_{Kp}, i.e. $\theta_K = \theta_{Kg} + \theta_{Kp}$. The general solution is obtained by setting $\mathbf{F}(t) = 0$ in **Eq. 6**, solving this gives

$$\theta_{Kg} = C\cos\left(\frac{\omega_K}{\sqrt{m_K}}t\right) + D\sin\left(\frac{\omega_K}{\sqrt{m_K}}t\right) \tag{8}$$

where C and D are constant. A Wronksian method is used to find the particular solution. For simplicity, let $a = \omega_T/\sqrt{m_T}$, $b = \omega_K/\sqrt{m_K}$, and the result is

$$\theta_{Kp} = -\frac{\omega_T^2}{m_K(a^2 - b^2)}(A\cos at + B\sin at) \tag{9}$$

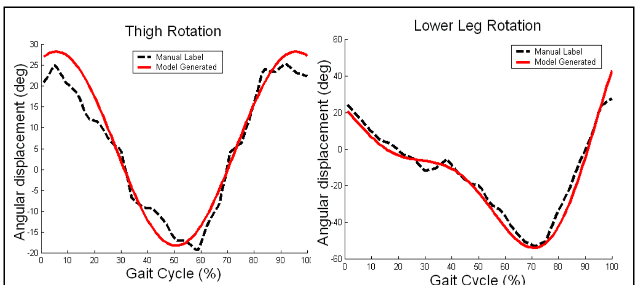
Recalling that $\theta_K = \theta_{Kg} + \theta_{Kp}$, by substituting **Eq. 8** and **Eq. 9**, the complete solution for θ_K yields the basic motion model for the lower leg rotation, which is

$$\theta_K = C\cos bt + D\sin bt - \frac{\omega_T^2}{m_K(a^2 - b^2)}(A\cos at + B\sin at) \tag{10}$$

The motion models derived earlier are not sufficient to guarantee a good approximation. To mimic the motion of the leg, parameters need to be included to increase the flexibility of the models. Phase (ϕ_T), amplitude (E), offset (M_T, M_K) and scaling (F) are added to the original motion models that serve as the foundation of describing the motion of the thigh (**Eq. 3**) and the lower leg (**Eq. 10**) and yield,

$$\theta_T = A\cos\left(\frac{\omega_T}{\sqrt{m_T}}t + \phi_T\right) + B\sin\left(\frac{\omega_T}{\sqrt{m_T}}t + \phi_T\right) + M_T \tag{11}$$

$$\theta_K = E\Big[C\cos(Fbt) + D\sin(Fbt) - \frac{\omega_T^2}{m_K(a^2 - b^2)}\big(A\cos(Fat + \phi_T) + B\sin(Fat + \phi_T) + M_T\big)\Big] + M_K \tag{12}$$



(a) (b)

Fig. 4: Sample output of the thigh and lower leg motion model superimposed with the manually labelled data.

An example of the waveform that can be produced by the thigh and lower leg motion models described by **Eqs. 11** and **12**, with appropriate parameter selection, is shown in **Fig 4**. As in **Fig. 2**, the structure of the response of the model appears very close to that of the manually labelled data. As expected the simple model does not match the thigh rotation precisely, but it can describe the gross motion of the lower leg, over one gait cycle.

2.3 Structural Model of Thigh and Lower Leg

Referring to **Fig. 3**, the structure of the thigh can be described by a point **h** that represents the hip and the line passing through **h** at an angle θ_T. The knee is then

$$\mathbf{k}(t) = \mathbf{h}(t) + l_T \mathbf{u}_T(t) \qquad \textbf{(13)}$$

where $\mathbf{u}_T(t)$ is the unit vector of the line direction, **h** is the position of the hip and l_T is the thigh length, as $\mathbf{u}_T(t)$ = [$-\sin\theta_T(t)$, $\cos\theta_T(t)$] and $\mathbf{h}(t)$ = [$h_x(0)$, $h_y(0) + S_y(t)$], where $h_x(0)$ and $h_y(0)$ are the initial hip coordinates. Decomposing **Eq. 13** into the x and y parts yields the coordinates of the knee point as,

$$k_x(t) = h_x(0) - l_T \sin\theta_T(t) \qquad \textbf{(14)}$$

$$k_y(t) = h_y(0) + S_y(t) + l_T \cos\theta_T(t) \qquad \textbf{(15)}$$

Similarly, the structure of the lower leg is given by a line which starts at the knee, that passes through **k** at an angle θ_k. The ankle **a** is

$$\mathbf{a}(t) = \mathbf{k}(t) + l_K \mathbf{u}_K(t) \qquad \textbf{(16)}$$

where $\mathbf{u}_K(t)$ is the unit vector of the line direction, $\mathbf{k}(t)$ is the position of the knee and l_K is the lower leg length, as $\mathbf{u}_K(t)$ = [$-\sin(\theta_K(t))$, $\cos(\theta_K(t))$] and $\mathbf{k}(t)$ = [k_x, k_y], where k_x and k_y is the point of the knee. Decomposing **Eq. 16** into x and y parts yields the coordinates of the ankle as,

$$a_x(t) = k_x(t) - l_K \sin(\theta_K(t)) \qquad \textbf{(17)}$$

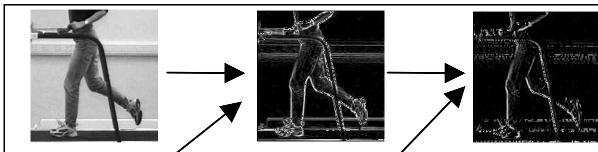
$$a_y(t) = k_y(t) + l_K \cos(\theta_K(t)) \qquad \textbf{(18)}$$

Hence, the motion model based on the biomechanics of walking and running with the dynamically coupled oscillator as the underlying concept has been derived. These equations form the basis of the model to be used within the feature extraction technique to find the moving lines that correspond to a subject's leg.

3. Feature Extraction

3.1 Low Level Feature Extraction

The subjects are filmed as video clips which are then digitized into individual image files and cropped to reduce computational cost. To reduce the complexity of the image, the Sobel edge operator is applied. A condition is applied, which effectively thresholds the x-component of the Sobel edge operator, to obtain only the leading edge. **Fig. 5**(a) shows the templates used to extract the (b) edge data and the condition applied to extract only the (c) leading edge.



$$M_x = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}, M_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \quad edge = \begin{cases} \sqrt{M_x^2 + M_y^2}, & M_x > 0 \\ 0, & M_x \le 0 \end{cases}$$

(a) Grey scale (b) Sobel edge (c) Leading edge

Fig. 5: The process of transforming a greyscale image to a single edge data via Sobel edge detection with a threshold condition on the *x*- component of the operator.

3.2 Evidence Gathering by Temporal Template Matching

A template, which is effectively a pair of moving lines that swing accordingly to the structural and motion models (described by **Eq. 11** and **Eq. 12)** are then matched to the leading edge data. Temporal template matching is an evidence gathering process where the template, which varies with time, is matched with a series of images to find the desired moving object in the sequence of images. For simplicity, the mass, m, in **Eq.11** and **Eq. 12**, is set to 1 and hence motion is dominated by the frequency, ω. No parameter selection is needed to differentiate between walking and running subjects (as it was in our earlier model[10]) due to the fact that this new model is invariant to walking and running gaits.

The vote is essentially the intensity value of that particular pixel that falls within the template. The peak of the accumulator array is the position where most pixels in the template match those in the image. As such, the peak is deemed to be the point where the "best fit" lines exist. The results are the relative vertical displacement of hip, the thigh and lower leg rotation, measured from the whole gait cycle. As depicted in **Fig. 6**, the result of this technique appears to extract well the thigh and lower leg motion without the need of parameter selection, despites the fact that walking and running are two totally different gaits. The extraction angles are precise in the regions where the legs cross and occlude each other. However, slight disparity may occur, as shown in the middle image of **Fig. 6**(a), due to the fact that this model is designed to extract the "best fit" leg motion throughout the gait cycle, but not to precisely model the biomechanics of these highly complex locomotion.

(a) Running | (b) Walking

Fig. 6: Leg motion extraction results of running and walking via evidence gathering by temporal template matching superimposed in white.

3.3 The Gait Signature

The gait signature of a particular gait cycle consists of the phase and the magnitude components made up of the Fourier description of the thigh and lower leg rotation measured from the gait cycle. Due to the Time Shift Theorem, when comparing the phase components of the transforms for different subjects, the time domain signal should start at the same point to ensure a valid analysis or comparison. Therefore, each gait cycle of different subjects starts at the same point, the conventional choice is at heel-strike. Although the magnitude spectra show variation among different subjects, in order to further increase the inter-class separability, the magnitude components are multiplied by the respective phase components[9], to yield the phase-weighted magnitude (PWM), which is used as the gait signature. If $\theta(n)$ is the discrete angle (of thigh or lower leg rotation) extracted by temporal template matching based on the model described and is transformed by the Discrete Fourier Transform to give the frequency components, $\Theta(e^{j\omega})$, then the PWM is

$$\mathrm{PWM}(\omega) = \left|\Theta\left(e^{j\omega}\right)\right| \bullet \angle\Theta\left(e^{j\omega}\right) \qquad \textbf{(19)}$$

Here the gait signature is formed from PWM components of the thigh rotation and PWM components of the lower leg rotation. The lower order components are chosen because the PWM components of the thigh and lower leg rotation are dominated by the lower order due to their greater magnitude values as shown in the polar plots in **Fig. 7**. Here, only the phase and magnitude (of the first three harmonics) of the leg motion of running is shown and is similar to those of walking. The magnitude of the higher order harmonics is relatively small and they are more likely to be dominated by noise. This is supported by a medical study which suggested that the maximum frequency content of human locomotion is 5Hz[11], that is, only the first five harmonics are sufficient to describe human locomotion.

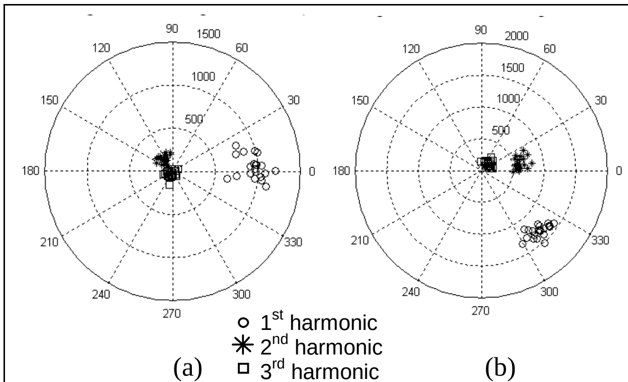


Fig. 7: The polar plot of the magnitude and corresponding phase components of the (a) thigh, and (b) lower leg rotation in the case of running.

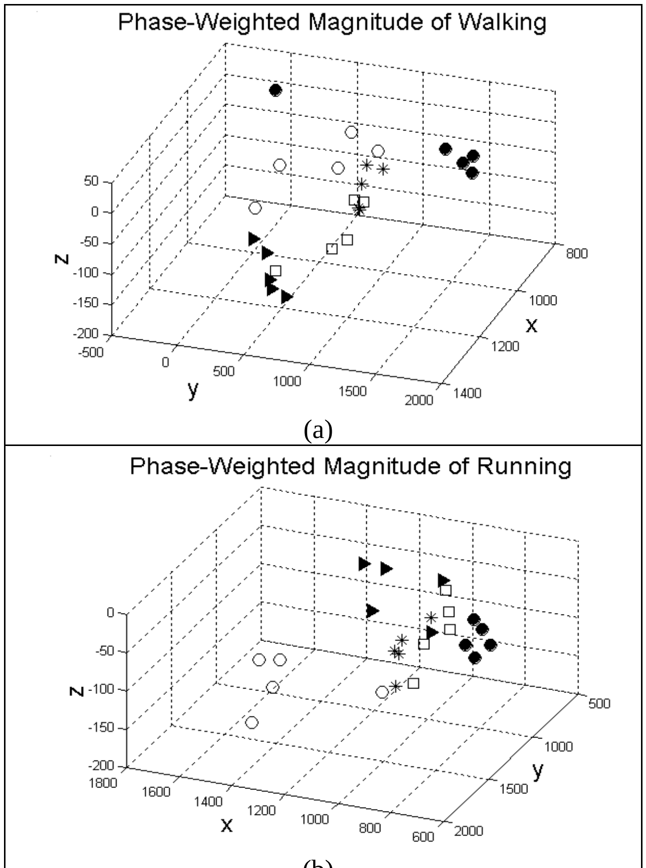


Fig. 8: Feature (phase-weighted magnitude) space of 5 walking and running subjects. x: 1st component of θ_T; y: 2nd component of θ_K ; z: 2nd component of θ_T .

4. Results

The database consists of fronto-parallel views of 7 subjects, with 5 samples each, walking and running at their preferred speeds on the treadmill in their own choice of clothing. Each sample consists of one gait cycle (i.e. two steps), between heel strikes of the same foot. The angular displacement of the thigh and lower leg rotation (of both walking and running) is extracted via temporal template matching with the dynamically coupled oscillator model as the underlying template. **Fig. 8** shows the feature space formed from the thigh and lower leg rotation. For visualisation purposes, only 3 of the PWM gait signature components are shown for 5 of the subjects. In general, clear class boundaries can be determined despite one or two stray samples.

Classification is achieved via the *k*-nearest neighbour (*k*-nn) and results are analysed by cross validation with the leave-one-out rule. **Table 1** shows the recognition rate achieved by this new model. In this case, using k=3 appears to be more prudent. The recognition rate based on Mahalanobis distance matric appears to improve over the basic Euclidean distance matric. Likewise, the recognition rate could be further improved by applying a more sophisticated and intelligent classifier. Note also that the feature-space clustering for running and walking occurs at a subject level and this suggests that an invariance relationship exists for subjects (as indeed suggested by our model). The feature space dispersion for the class is different from that for the subjects, suggesting that a general invariance relationship for human walking and running is unlikely.

Table 1: The recognition rates for walking and running via *k*-nn with Euclidean and Mahalanobis distance.

	Walk(%)		Run(%)	
k	Euclidean	Mahalanobis	Euclidean	Mahalanobis
1	55	60	63	63
3	66	74	71	77

5. Conclusions and Future Work

A new analytical model based on a dynamically coupled oscillator has been derived and shown to be able to describe both walking and running gaits without the need for parameter selection. This technique provides a consistent framework to extract running and walking subjects and yields a fully automatic gait recognition system for walking and running. With just a basic classifier, the technique achieves a reasonable recognition rate for walking and running subjects. We shall not be disconcerted by the recognition rate presented here, as our main objective is to develop a dynamic model which can handle walking and running gaits that is well suited for an automatic gait recognition system. Naturally, using a more sophisticated classifier could easily increase the recognition rate. Future work intends to investigate the feature set selection to increase the recognition rate based on the fundamental attributes that underlie the kinematics of the gaits and to determine the invariant mapping for walking and running. Due to the high inter-subject variability, we expect at best just be able to develop mapping for individual subjects, not a generic mapping across the population.

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References

[1] S.A. Niyogi and E.H. Adelson. Analyzing and Recognizing Walking Figures in XYT. *CVPR*, pp 469-474, 1994.

[2] H. Murase and R. Sakai. Moving Object Recognition in Eigenspace Representation: Gait Analysis and Lip Reading. *Pattern Recognition Letters*, **17**, pp 156-162 1996.

[3] J. Little and J. Boyd, Recognizing People by Their Gait: The Shape of Motion. *Videre: Journal of Computer Vision Research*, Article 1, **1**(2), Winter 1998.

[4] P.S. Huang, C.J. Harris and M.S. Nixon. Human gait recognition in canonical space using temporal templates. *IEE Pros: VISP*, **146**(2), pp 93-100, 1999.

[5] C.B. Abdelkader, R. Cutler, H. Nanda and L. Davis. Eigen Gait: Motion-based Recognition of People using Image Self-Similarity, *3rd Proc. AVBPA 2001*, pp284-294, June 2001.

[6] J.D. Shutler, M.S. Nixon and C.J. Harris, Statistical Gait Description via Temporal Moments, *Proc. SSIAI 2000, Austin, Texas*, pp 291-295, April 2000.

[7] J.W. Davis, Visual Categorization of Children and Adult Walking Styles, *3rd Proc. AVBPA 2001*, pp295-300, June 2001.

[8] A.Y. Johnson and A.F. Bobick, A Multi-view Method for Gait Recognition Using Static Body Parameters, *3rd Proc. AVBPA 2001*, pp 312-317, June 2001.

[9] D. Cunado, J.M. Nash, M.S. Nixon and J.N. Carter. Gait Extraction and Description by Evidence-Gahtering. *2nd Proc. AVBPA 1999*, pp 43-48, March 1999.

[10] C.Y. Yam, M.S. Nixon and J.N. Carter, Extended Model-Based Automatic Gait Recognition of Walking and Running, *3rd Proc. AVBPA 2001*, pp278-283, June 2001.

[11] C. Angeloni, P. O. Riley and D. E. Krebs. Frequency Content of Whole Body Gait Kinematic Data, *IEEE Transactions on Rehabilitation Eng.*, **2**(1), pp 40–46, 1994.