Performance Analysis on New Biometric Gait Motion Model

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Abstract

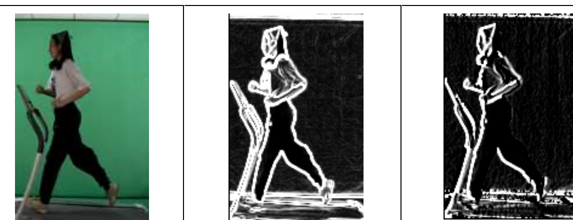
Recognising people by the way they walk and/or run is new. A novel analytical model which is invariant to human gait of walking and running is developed based on the concept of dynamically coupled oscillators and the biomechanics of human walking and running. It serves as the foundation of this automatic person recognition system. The effects of noise and low resolution have been evaluated on the largest data set of its kind. This is useful as security camera footage is usually prone to noise and of poor resolution. The gait signature is formed from the Fourier description of the thigh and lower leg rotation. Angles of rotation are extracted via temporal template matching across the whole image sequence. Classification is done via the k-nearest neighbour and cross-validated with the leave-one-out rule. The promising recognition rates for both walking and running suggest the high potential of this technique and using gait as the cue for person identification in practical applications. Future work will focus on understanding the features used to create the gait signature in order to further improve the recognition rate and will determine the invariance attributes for walking and running.

1. Introduction

Using gait, including both walking and running, as a cue to identifying people is motivated by publicised crimes where the camera footage reveals the way a criminal walks into a crime scene and runs to escape. This technique is particularly useful when there is no other biometric evidence such as a fingerprint, or when the face is disguised or covered with a mask. Gait has been explored as a biometric only recently. There are also studies on gender [1] and age [2] discriminations by the style of walking. Many statistical approaches have been deployed to recognise people by their walk, such as using spatio-temporal pattern [3] , velocity moments [4], combining Canonical Analysis and eigenspace [5], static body parameters [6] and image self-similarity [7]. Nevertheless, model-based approach is relatively rare. The first model-based approach in using gait (walking) as a biometric [8] proved successful. However, only recently has the possibility of employing walking and running gait as biometrics [9] been explored. Later, a more efficient model which is invariant to the biomechanically distinct gaits of walking and running [10] suggests the potential of using both the gait of walking and running to recognise people. Here, we investigate further the effect of noise and low resolution, which is usually the case for footage captured by the surveillance cameras, on the largest data set of its kind.

2. Feature Extraction

Subjects are filmed as video clips which are then digitised into individual colour image files and cropped to reduce computational cost. A condition, which effectively thresholds the horizontal component of the Sobel edge operator, is applied to obtain only the leading edge, see **Fig. 1**. In this way, low-level feature extraction concentrates on those parts of the clothing that adhere most to the limbs, when walking and running.



(a) (b) (c)

Fig. 1: Low level processing - (a) Colour image; (b) Sobel edge; (c) Leading edge.

In order to extract the rotation angles made by the thigh and the lower leg, we need to have a model of these motions to serve as the underlying template for an evidence gathering process. The vertical hip displacement is described by

$$S_y(t) = A_y \sin(2\omega_y t + \phi_y) \tag{1}$$

where A_y is the amplitude of the vertical oscillation, ω_y is the fundamental frequency, and ϕ_y is the relative phase shift. Due to the fact that the subjects are walking and running on a motorised treadmill at a constant speed, and the resolution of images used, the horizontal motion of the hip is insignificant to be ignored. The thigh and the lower leg motion models [10] are derived from dynamically coupled force driven oscillators where two pendula are joined in series (**Fig. 2**) and can be described by **Eqs. 2** and **3** as:

$$\theta_T = A\cos(at + \phi_T) + B\sin(at + \phi_T) + M_T \qquad \textbf{(2)}$$

$$\theta_K = E\left[C\cos(Fbt) + D\sin(Fbt) - \frac{\omega_T^2}{m_K(a^2 - b^2)}\left(A\cos(Fat + \phi_T) + B\sin(Fat + \phi_T) + M_T\right)\right] + M_K \qquad \textbf{(3)}$$

where $a = \omega_T / \sqrt{m_T}$, $b = \omega_K / \sqrt{m_K}$. A, B, C and D are constants, and t is the time index which varies from 0 to 1, where 1 is the completion of a gait cycle and hence, invariant to speed. To mimic the motion of the leg, parameters need to be included to increase the flexibility of the models which is consist of amplitude (E), offset (M_T, M_K) and a scale parameter (F) variables.

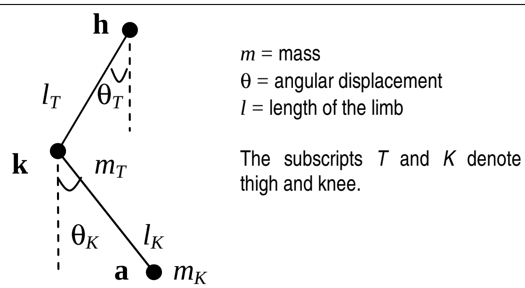


Fig. 2: The model of the thigh and lower leg: an upper pendulum models the thigh and the lower pendulum models the lower leg, connected at the knee joint.

Referring to **Fig. 2**, 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

$$\mathbf{k}(t) = \mathbf{h}(t) + l_T\mathbf{u}_T(t) \qquad \textbf{(4)}$$

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. 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

$$\mathbf{a}(t) = \mathbf{k}(t) + l_K\mathbf{u}_K(t) \qquad \textbf{(5)}$$

where $\mathbf{u}_K(t)$ is the unit vector of the line's 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 are the co-ordinates of the knee.

The angle rotations of the thigh and the lower leg are extracted by an evidence gathering technique. A template (which is effectively a pair of moving lines that swing according to the structural motion models) is 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 **Eqs. 2** and **3**, is set to 1 and hence motion is dominated by the frequency, ω. No parameter selection is necessary (as it was in an empirical model [9]) since 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.

(a) Running

(b) Walking

Fig. 3: Leg motion extraction results of running and walking via evidence gathering by temporal template matching superimposed in white.

The angle extraction here is a two-pass evidence gathering process where the first pass aims to get the best parameters for the motion models. Then a refined individual frame match is carried out to extract the most accurate possible angle from each frame, which in turn makes up the series of moving lines representing the thigh and the lower leg. As such, we measure the deviation from each individual's unique norm. As depicted in **Fig. 3**, this technique appears to extract well the thigh and lower leg, 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.

3. Gait Signature

The gait signature of a particular gait cycle consists of the phase and the magnitude components of the Fourier description of the thigh and lower leg rotation measured from the gait cycle. By the *Time Shift Theorem*, to compare phase, the time domain signals should be aligned. Therefore, each gait cycle is arranged to start at the same point, which is the minimum of the thigh rotation and the corresponding point of time of the lower leg motion. 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, 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 the evidence gathering technique 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

$$\mathrm{PWM}(\omega) = \left|\Theta\left(e^{j\omega}\right)\right| \bullet \angle\Theta\left(e^{j\omega}\right) \qquad (5)$$

where ● denotes multiplication of each element in the vector.

Here the gait signature is formed from the lower PWM components of the thigh and lower leg rotation. They are dominated by the lower order due to their greater magnitude values as shown in the polar plot in **Fig. 4**. Here, only the PWM (of the first three harmonics) of the lower leg motion of 20 running subjects is shown. The magnitude of the higher order harmonics is relatively small, as such more likely to be dominated by noise. Features shown confirm the general trend of the leg motion (the relative size of the harmonics) with some variation across the population, as expected.

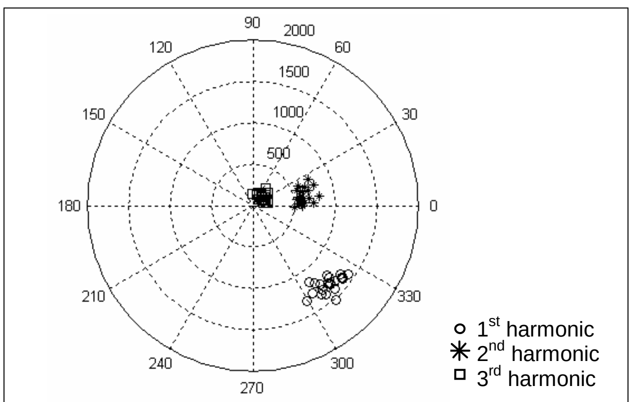
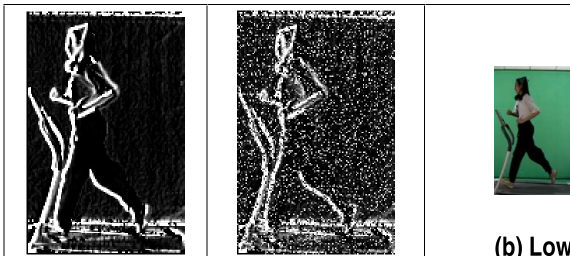


Fig. 4: Polar plot for the PWMs of lower leg when running.

4. Performance Analysis

The database consists of fronto-parallel views of 20 subjects walking and running on a motorised treadmill at their preferred constant speeds in their own choice of clothing, with 6 samples of walking and running for each subject. Angle extraction is then done on the edge data and acquired via the evidence gathering technique, with the structural motion models as the underlying template. Analysis was carried out on clean images (130x190), images with 25% grey scale random noise added to the edge images and low resolution images which were half of the original size (**Fig. 5**). Note that a unique advantage of gait concerns ability at a distance where other biometrics are obscured. In the low resolution images, the ears, iris and face cannot be seen clearly.



(a) Edged image | (b) 25% Greyscale noise | (b) Low resolution (65 x 95)

Fig. 5: Images used for performance analyses.

Fig. 6 shows the signature formed from the thigh and lower leg rotation. For visualisation purposes, only 3 PWMs of 5 subjects are shown. Different patterns of data points represent different subjects, each subject with 6 samples of walking and running. As depicted, there are well-defined intra-class boundaries and the signatures are densely clustered, especially for the case of walking. As expected, the walking gait is considered more consistent relative to running gait. The features also appear to have an individual mapping between the feature space of walking and running on an individual class basis.

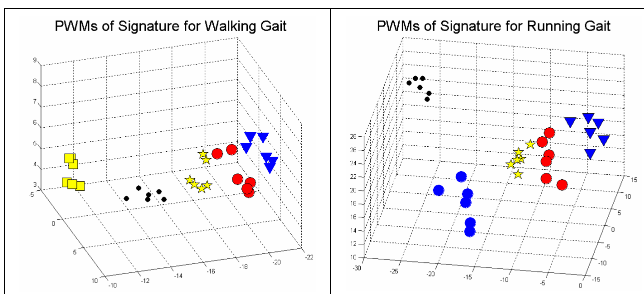


Fig. 6: PWMs of 5 subjects walking and running.

Classification is done via the *k*-nearest neighbour (*k*-nn) and cross validated with the leave-one-out rule, with *k*=1, 3 and 5. As depicted in **Table 1**, the recognition rate of running is higher than walking due to the fact that the running style has more variability whereas walking style has less variability across the population. As expected, the recognition rate decreased when 25% grey scale salt and pepper noise was added. The rate also decreased slightly when the technique was evaluated on low resolution images. That rate does not decrease as much as when tested with noise could be due to measurement of angle of leg rotation, which is invariant to scale. However, we should expect the recognition rate to reduce with poor resolution, and to fail when the resolution is too low.

Table 1: Performance analyses of walking and running

	Walk (%)			Run (%)		
k	Clean	Noise	Low Resolution	Clean	Noise	Low Resolution
1	84.2	60.8	76.7	91.7	70.0	86.7
3	67.5	41.7	61.3	84.2	55.8	75.0
5	55.0	33.3	48.1	68.9	48.1	62.8

5. Conclusions and Future Work

Performance analyses of grey scale noise and low resolution have been evaluated on the largest gait database of its kind. The experiment shows the potential of this novel technique in terms of practicability and using human gait, including walking and running as a cue for individual identification. With a simple classifier, this new technique achieves a promising recognition rate. Naturally, a more sophisticated classifier could further improve the rate. Interestingly, the increased variability of running suggests that it might be a more potent recognition cue. This is consistent across the performance analyses. The effect of noise suggests a need for refining the technique whereas with low resolution images, the subjects can still be recognised with performance equalling to that of human vision. Future work will focus on the feature space to further improve the recognition rate and to determine invariant properties of walking and running and their use in applications of this new biometric.

6. References

[1] L. T. Kozlowski and J. E. Cutting, "Reconizing the Sex of a Walker from a dynamic Point-Light Display," *Perception and Psychophysics*, vol. 21, pp. 575-580, 1977.

[2] J. W. Davis, "Visual Categorization of Children and Adult Walking Styles," *3rd Proc. Audio- and Video-Based Biometric Person Authentication*, pp. 295-300, 2001.

[3] S. A. Niyogi and E. H. adelson, "Analyzing and Recognizing Walking Figures in XYT," *In Proceedings Conference of Computer Vision and Pattern Recognition*, pp. 469-474, 1994.

[4] J. D. Shutler, M. S. Nixon, and C. J. Harris, "Statistical Gait Recognition via Temporal Moments," *4th IEEE Southwest Symposium on Image Analysis and Interpretation, Texas*, pp. 291-295, 2000.

[5] P. S. Huang, C. J. Harris, and M. S. Nixon, "Recognising Humans by Gait via Parametric Canonical Space," *Artificial Intelligence in Engineering*, vol. 13, pp. 359-366, 1999.

[6] A. Y. Johnson and A. F. Bobick, "A Multi-View Method for Gait Recognition Using Static Body Parameters," *3rd International Conference AVBPA*, pp. 301-311, 2001.

[7] C. B. Abdelkader, R. Cutler, H. Nanda, and L. Davis, "EigenGait: Motion-Based Recognition Using Image Self-Similarity," *3rd International Conference AVBPA*, pp. 289-294, 2001.

[8] D. Cunado, M. S. Nixon, and J. N. Carter, "Automatic Gait Recognition via Model-Based Evidence Gathering," *Proc. AutoID99: IEEE Workshop on Automated ID Technologies Summit*, pp. 27-30, 1999.

[9] C.-Y. Yam, M. S. Nixon, and J. N. Carter, "Extended Model-Based Automatic Gait Recogniton of Walking and Running," *3rd Proc. Audio- and Video-Based Biometric Person Authentication*, pp. 284-294, 2001.

[10] C.-Y. Yam, M. S. Nixon, and J. N. Carter, "Gait Recognition by Walking and Running: A Model-based Approach," *5th Proc. Asian Conference on Computer Vision*, 2002.

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