A Statistical Registration of Scale-Changing and Moving Objects with Application to the Human Gait Authentication

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1 Introduction

A study on the human gait is important in the fields of the biometrics study and the sports/health managements for planning optimal trainings. Olshen *et al.* (1989) proposed the bootstrap estimation for confidence intervals of the functional data with application to the gait cycle data observed by the motion capture system. Kaziska and Srivastava (2007) proposed the method based on the data matching techniques using the dynamic time warping of human silhouettes. Gait analysis is mainly based on motion capture system and video data.

The motion capture system can give the precise measurements of trajectories of moving objects, but it requires the laboratory environments and we cannot be used this system in the field study. On the other hand, the video camera is handy to observe the gait motion in the field study, but such data has many restrictions on analysis based on the filming conditions. In particular, the video data filmed from the frontal-view is difficult to analyze, because the subject getting closer to the camera, and observed data includes the scale-changing parameters. To cope with this, Okusa *et al.* (2011) proposed a registration for scales of moving object using the method of nonlinear least squares with application to the gait analysis assuming constant speed.

In this study, focusing on the human gait cycles, we consider the human gait modeling based on simple gait structure. We estimate the parameters of the human gait cycles using the method of nonlinear least squares (Okusa *et al.* 2011). We can also show that estimated parameters may be used for the human gait recognition. We apply a nearest-neighbor classifier, using the estimated parameters, to perform the human gait recognition, and present results from an experiment involving 55 subjects. As a result, our method shows 96.3% recognition rate, that has the better performance compared to other methods.

2 Preprocessing

The video data contain background information. We separate moving object from background information using inter-frame subtraction method

$$(1) \qquad \Delta^{(T)} = |I^{(T+1)} - I^{(T)}|, \quad T = 1, ..., (n-1), \quad \Delta^{(T)}(p,q) = \begin{cases} 1 & (\Delta^{(T)}(p,q) > 0) \\ 0 & (\text{Otherwise}). \end{cases}$$

Here, $\Delta^{(T)}$ is an inter-frame subtraction image, $I^{(T)}$ is the video data image at frame T, (p,q) is the pixel number.

2.1 Subject Length Calculation

Inter-frame subtraction image (see Figure 1) is difficult to measure the time-series behavior of the subject width and height. Let us suppose that inter-frame subtraction image is binary matrix. We can measure the subject height and width by integration calculation of row and column at each frame as shown in Figure 2.

Figure 1: Inter-frame subtraction image

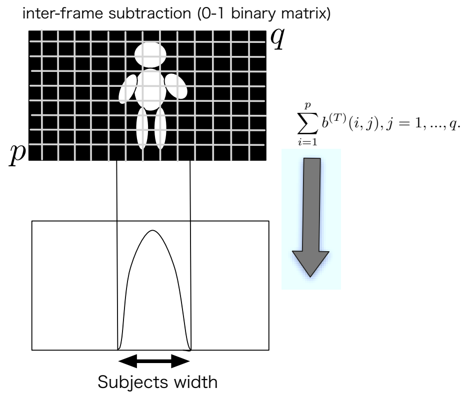

Figure 2: Subject Length Calculation

In this study, we use this value as subject width and height.

3 Methods

3.1 Relation between camera and subject

Figure 3 shows a relation between camera and subject. We can assume simplified camera structure. We consider the virtual screen exists between observation point and subject, and we define subject length on the virtual screen y_i at i-th frame($i = 1, ..., n$).

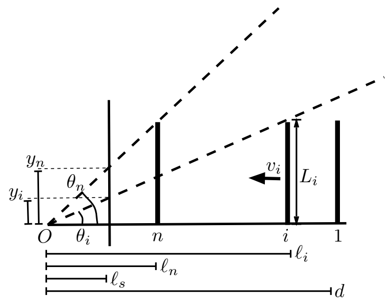

Figure 3: Relation between camera and subject

Here we use ℓ_i as distance between observation point and subject at i-th frame, ℓ_s as distance between observation point and virtual screen, θ_i as subject angle of view from observation point at i-th frame, d as distance between observation point and 1st frame, v_i as subject speed at i-th frame. Okusa *et al.* (2011) defined the subject length L was constant. We assume that L has the time-series behavior and we define L_i is the subject length at i-th frame.
y_i at i-th frame depends on θ_i as shown in Figure 3

(2) $$y_i = \ell_s \tan \theta_i.$$

Similarly, the subject length at i-th frame is

$$L_i = \ell_i \tan\theta_i. \tag{3}$$

From Eq.(2), Eq.(3), ratio between y_n and y_i is

$$\frac{y_n}{y_i} = \frac{L_n\ell_i}{L_i\ell_n} \tag{4}$$

Frame interval is equally-spaced (29.97fps), thus, travel time $(n-i)$ from i-th frame is $(\ell_i - \ell_n)/\frac{1}{(n-i)}\sum_{k=1}^{(n-i)} v_k = (n-i)$. Okusa *et al.* (2011) assumed the average speed is constant. We can assume that average speed from i-th frame is $\frac{1}{(n-i)}\sum_{k=1}^{(n-i)} v_k = \bar{v}$, therefore ℓ_i is $\ell_i = \ell_n - \bar{v}(n-i)$. We substitute ℓ_i to Eq.(4)

$$y_i = \frac{M_i\gamma}{\{\gamma - (n-i)\}} y_n + \epsilon_i, \tag{5}$$

where γ is $\ell_n/\bar{v}$, M_i is L_i/L_n, ϵ_i is noise. From Eq.(5), predicted value $\hat{y}_i^{(n)}$ is registration from i-th frame's scale to n-th frame's scale

$$\hat{y}_i^{(n)} = \frac{\{\gamma - (n-i)\}}{M_i\gamma} y_i. \tag{6}$$

We estimate the "scale parameter", "movement parameter" by next 2-steps.

3.2 1st step: Estimation of scale parameter γ

From Eq.(5), scale parameter is γ. Solve Eq.(5) for γ shows

$$\gamma = \frac{y_i(n-i)}{y_i - M_i y_n}. \tag{7}$$

Here γ is the ungaugeable parameter, and we estimate it using nonlinear least squares method

$$S(\gamma, M_i) = \sum_{i=1}^{n} \left\{ y_i - \frac{M_i\gamma}{\{\gamma - (n-i)\}} y_n \right\}^2. \tag{8}$$

We set the initial value γ to arithmetic mean value of Eq.(7), and M_i to 1 (Okusa *et al.* (2011)).

3.3 2nd step: Modeling of M_i

M_i is a movement model of the subject. If a subject is the rigid body, movement model M_i is constant. Human gait, on the other hand, is not a constant because the subject body is moving wildly, M_i needs the movement model.

3.3.1 Human gait modeling: arm swing

Collins *et al.* (2009) has reported that arm swing is an very important role in the gait motion using simple gait model. We consider the human gait modeling based on Collins *et al.* (2009) model (see Figure 4).

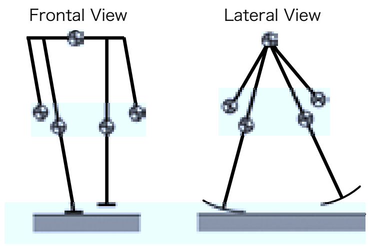

Figure 4: Our gait model

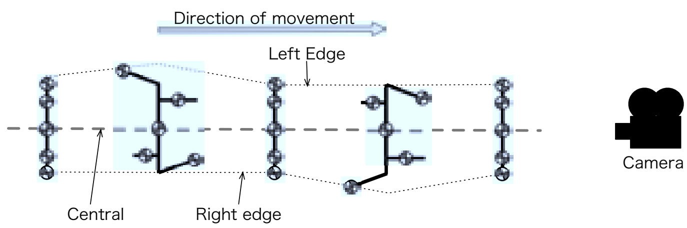

Figure 5: Our gait model: arm swing

Collins *et al.* (2009) model only assumed the arm swing to back and forth. Now our model can assume arm swing to an oblique direction (see Figure 5). It seems reasonable to think that arm is single pendulum. Arm swing model is

$$y_i = \frac{\gamma}{\gamma - (n-i)}\{a_1\tau(fi+Q_1, g_1)\sin\psi_1 + a_2\tau(fi+Q_2, g_2)\sin\psi_2\}y_n + \epsilon_i \tag{9}$$

$$\tau(x,g) = \begin{cases} \cos(x)+g & (\cos(x)+g>0) \\ 0 & (\text{Otherwise}). \end{cases}$$

Here $a_1\tau(fi+Q_1, g_1)\sin\psi_1$ and $a_2\tau(fi+Q_2, g_2)\sin\psi_2$ is right and left arm model. From Eq.(9), we estimate each gait parameter using nonlinear least squares method

$$S(\gamma, f, P_{1,2}, Q_{1,2}, g_{1,2}) = \sum_{i=1}^{n}\left\{y_i - \frac{\gamma\,\{P_1\tau(fi+Q_1,g_1)+P_2\tau(fi+Q_2,g_2)\}}{\gamma-(n-i)}y_n\right\}^2 \tag{10}$$

$$s.t.$$

$$0 < f < 1.$$

We combine the parameters $a_1, \sin\psi_1$ as P_1, and $a_2, \sin\psi_2$ as P_2. Here γ is scale parameter, we set the initial value to $\hat{\gamma}$ from 1st step. f is gait cycle frequency, we set the initial value to 0.5 (Logan *et al.* (2010) and Wendt *et al.* (2010) has reported human gait cycle frequency is found in 0-1 Hz). $P_{1,2}$ are arm swing amplitude parameter, we set the initial value to range of registration value $\hat{y}_i^{(n)}$ from 1st step. $Q_{1,2}$ are arm phase parameters, we set the initial value to $0, \pi$ (Ehara (2006) has reported ideal human gait phase is antiphase). $g_{1,2}$ are arm cover parameters, we set the initial value to 0.

4 Experimental Details and Results

To demonstrate the effectiveness of our method, we conducted two sets of experiments, assessing the proposed method in 1) gait parameter estimation and 2) human gait authentication.

4.1 Estimation of Gait Parameter

In this experiment, we used 10 steps gait data (24 aged man, height: 174cm) and apply to our method. Figure 6 is plot of the subject width(pixel) vs frame no. Here dotted line represent fitted value of Sec 3.2 model, continuous line represent fitted value of Sec 3.3 model. Table 1 is AIC and RSS value of first order regression, second order regression, Sec 3.2 model, Sec 3.3 model.

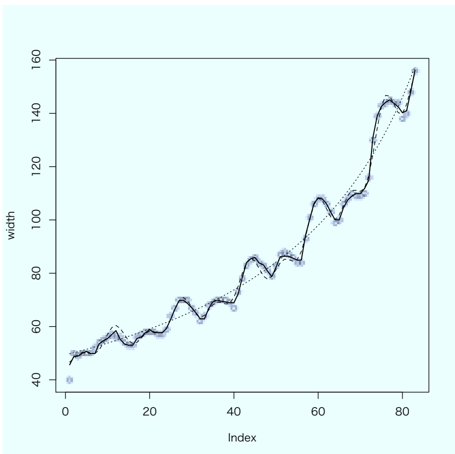

Figure 6: Plot of the subject width(pixel) vs frame no., fitted line

Table 1: AIC and RSS

	AIC	RSS
First order regression	614.49	7421.37
Second order regression	528.29	2564.73
Sec. 3.2 model	511.99	2158.7
Sec. 3.3 model	419.84	390.09

Figure 6. and Table 1. shows our method has the good performance.

4.2 Gait Authentication

From a practical perspective, the method based on the video data is very important authentication technique, data not require the subject to help this system. For instance, face recognition is one of the famous authentication techniques using video data. However, it needs strong learning (Zhou *et al.* 2006). Gait authentication, on the other hand, is a viable alternative (Barnich & Droogenbroeck 2009).

In this experiment we took movie of 55 subjects walking video image data from frontal-view (10 steps, Male: 46 (average height: 173.24cm, sd: 5.64cm), Female: 9 (average height:156.25cm, sd: 3.96cm), see Figure 7,8) and apply to our proposed method for the gait authentication.

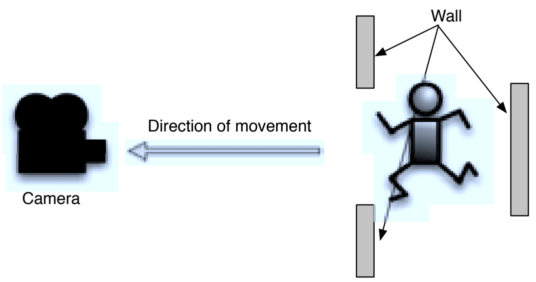

Figure 7: Experimental Circumstance

Figure 8: Example of Authentication Data

Gait data captured in twice, we set first data as supervised and second data as test data. We estimate gait parameters using method of Sec 3.3. K-NN method apply to the estimated gait parameters for authentication.

Table 2. shows recognition rate of gait authentication. We compared our method with Barnich & Droogenbroeck (2009) method. They have reported that frontal-view gait authentication is an effective approach. Their approach based on shape analysis and histogram.

Table 2: Recognition rate of gait authentication

	Recognition rate
Proposed method	96.36%
Barnich & Droogenbroeck (2009)	78.18%

Table 2. shows our method has the better performance compared to Barnich & Droogenbroeck (2009) method.

5 Conclusions

In this article, focusing on the human gait cycles, we consider the human gait modeling based on simple gait structure. We estimate the parameters of the human gait cycles using the method of nonlinear least squares (Okusa *et al.* 2011). We also show that estimated parameters may be used for the human gait authentication. Our method has the better performance compared to other method.

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