Tracking of Thigh Flexion Angle during Gait Cycles in an Ambulatory Activity Monitoring Sensor Network[1)]

DONG Liang[1] WU Jian-Kang[1,2] BAO Xiao-Ming[1] XIAO Wen-Dong[1]

[1](*Institute for Infocomm Research, 21 Heng Mui Keng Terrace, Singapore* 119613, *Singapore*)

[2](*Graduate School, Chinese Academy of Sciences, Beijing* 100049)

(E-mail: ldong@i2r.a-star.edu.sg, jiankang@i2r.a-star.edu.sg, baoxm@i2r.a-star.edu.sg, wxiao@i2r.a-star.edu.sg)

Abstract An accelerometry-based gait analysis approach *via* the platform of sensor network is reported in this paper. The hardware units of the sensor network are wearable accelerometers that are attached at the limbs of human body. For the specific task of gait analysis, flexion angles of the thighs during gait cycles are computed. A Kalman filter is designed to estimate the flexion-extension angle, angular velocity of the thigh using the output of the wearable accelerometers. The proposed approach has been applied to four subjects and the performance is compared with video-based approach. Comparative results indicate that with the proposed Kalman filter, the sensor network is able to track the movement of the thighs during gait cycles with good accuracy and simultaneously detect major gait event of foot contact from the waveform of the angular velocity.

Key words Gait analysis, sensor networks, Kalman filter, thigh flexion angle

1 Introduction

The application of sensor network on body activity monitoring is a fresh research endeavor. The attraction of this approach lies in its ambition, where networked sensors are worn on mobile human body, rather than placed on fixed locations. The mobility of sensors makes the sensor network very flexible and powerful in dealing with dynamic processes. This is especially true for body activity monitoring where the subjects are free to move around with little *a priori* knowledge. Most previous endeavors for body activity monitoring are based on video/image.

Gait analysis is the technique of tracking, monitoring, recognition and understanding of different walking patterns such as walking along a straight line, walking along a slope, limping, jogging, *etc.* Gait analysis is important because it helps to identify the underlying causes for walking abnormalities in patients with cerebral palsy, stroke, head injury and other neuromuscular problems, helps to determine the best course of treatment, helps to quantify improvement resulting from medical interventions, and helps to predict subsequent events such as falls. Gait analysis can also be used for animation and personal identification.

A typical vision-based gait analysis is conducted as follows: Some markers are attached at both sides of a person, especially at the legs and trunk. Several cameras record the body movement while the person is walking. During the image processing phase, the markers are segmented out of the image. Based on the trace of the markers, flexion angles of major body segments are derived and gait patterns are reconstructed. Using this approach, the gait features can be accurately captured and further analyzed. On the other hand, the disadvantages of video/image based gait analysis are also obvious. First, special makeup (marker) is always necessary for effective image processing. It is impractical to be applied to free-living subjects. Second, such experiment can only be conducted in restricted environment over short time. Ambulatory activity monitoring is not feasible. Third, the computational load involved in image processing is heavy. Video/image based activity monitoring is difficult to be made real-time.

To overcome the shortcomings of the video/image based methods, the sensor network with wearable sensors is applied for gait analysis in this paper. Over the past few years, gait analysis has advanced considerably chiefly due to the new features of the gait that have been extracted and studied. Some of these features are well-known such as walking velocity, walk ratio (gait cycle time), cadence (step rate), acceleration, ground reaction measurement and joint angles[1], while the other features may be quite fresh, which include foot contact (heel strike)[2], foot pressure[3], acceleration root mean square, harmonic ratio[4], double supports[5], stance-swing phase[6], foot inertial[7], biped symmetry[8], *etc.* Among the various features, joint angle is always treated with high significance for determining body posture

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and movement[9,10]. For gait analysis, three joint angles: hip angle, knee angle and heel angle play the key role. If the values of these angles can be computed at every moment during walking, dynamics of a gait cycle are largely determined[11].

For the ambulatory activity monitoring sensor network discussed in this paper, wearable biaxial accelerometers are used as activity detectors. The thigh flexion angle, which is closely associated with the hip angle and knee angle, is the target of investigation. A Kalman filter (KF) is designed to estimate the thigh flexion angle, angular velocity, vertical and horizontal accelerations from the output of the wearable accelerometers that are attached at fixed positions of the thighs. Experimental results indicate that by using the proposed KF, the ambulatory activity system is able to track the thigh flexion angle effectively.

The rest of the paper is organized as follows. A brief introduction to the activity monitoring sensor network is given in Section 2. The approach of gait segmentation is presented in Section 3. This is followed by a detailed description to the KF-based angle tracker in Section 4. The performance of the KF is evaluated via experiments in Section 5 and the concluding remark is given in Section 6.

2 An overview of the activity monitoring system

In the Institute for Infocomm Research (I^2R), an activity monitoring system based on sensor network is developed to track and understand body activities of free-living subjects under monitoring. The basic structure of the activity monitoring system is depicted in Fig. 1.

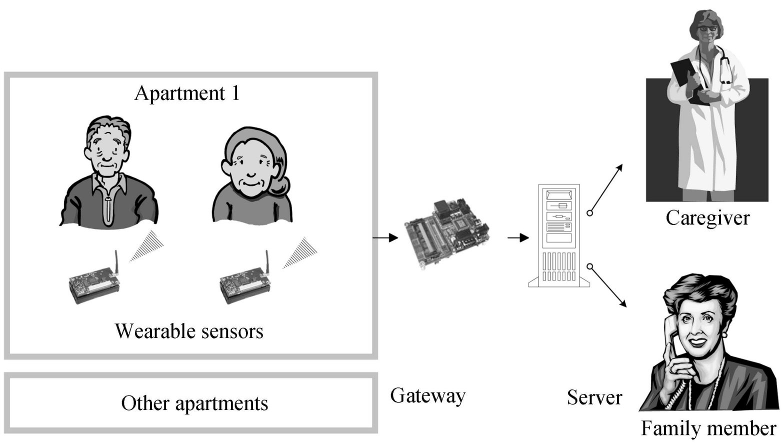


Fig. 1 An overview of the activity monitoring sensor network

The activity monitoring sensor network consists of wearable sensors, gateway and server. The wearable sensor used in the system is Crossbow MicaZ biaxial accelerometer (MTS310)[12]. The workflow of the system is briefed as follows: The wearable sensor samples x and y accelerations (horizontal and vertical accelerations with respect to the accelerometer coordinates) and output them to the gateway. Programs running in the gateway carry out activity identification and activity tracking. The basic body status (sitting, lying down, standing, and walking), critical events (falling down and abnormal walking patterns), and key position indicators (joint angles, trunk flexion angles, *etc.*) are sent to a centralized database server. An authorized subscriber such as a caregiver or family member of the wearer may access these data and learn what the person is doing on a real-time basis. Such an activity monitoring sensor network has been applied to identify basic body status and track body postures with some success[8,13]. In this paper, the swing of the thighs during a gait cycle is studied. It is expected to learn how the thigh flexion angle changes with simple hardware settings, say, only one accelerometer affixed to one limb. In our scenario, two sensors are attached to the exterior sides of both thighs as depicted in Fig. 2(a).

While the person is walking, the sensors measure vertical (y) and horizontal (x) accelerations at the sampling rate of 25Hz. These acceleration values are then put through gait segmentation and thigh flexion angle estimation that to be mentioned in Section 3 and 4.

3 Gait segmentation

As the first step of gait analysis, individual gait cycles are segmented out of a sequence of gait cycles. A gait cycle is generally referred to as the interval between two subsequent left foot contacts[2]. One of the gait segmentation methods is the detection of heel strike using the vertical acceleration[2,8]. A heel strike is the moment that the foot contacts ground. It indicates the end of one gait cycle or the beginning of a new gait cycle. A heel strike brings forward prominent upward acceleration in the waist and legs. In the waveform of the vertical acceleration of the thigh, there is a valley at the moment when a heel strike occurs, which is manifested in Fig. 3. By detecting the local minimum points in the waveform and by investigating the spectrum of the waveform, it is possible to segment each gait cycle with good accuracy. Detailed study on this issue is presented in [2] and [8].

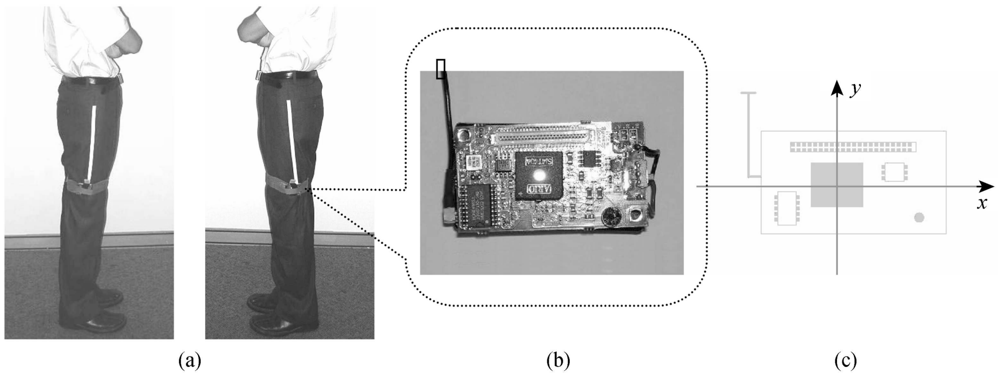


Fig. 2 (a) Placement of the accelerometers (b) Biaxial accelerometer (c) Coordinates of the accelerometer

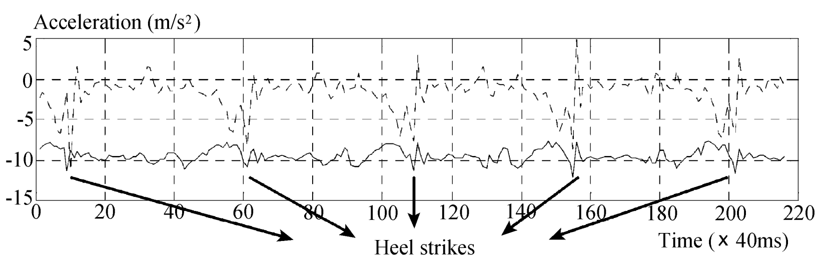


Fig. 3 The waveforms of y-acceleration (solid) and x-acceleration (dotted) measured by the accelerometer

Based on the nature of human walking, a gait is decomposed into three phases as depicted in Fig. 4: Phase 1 is foot rising. This is the period when the foot is raising from the ground to start a step; Phase 2 is swing forward, which is the interval that the thigh moves forward; and Phase 3 is heel strike, during which the foot is touching ground to signify the end of the gait cycle.

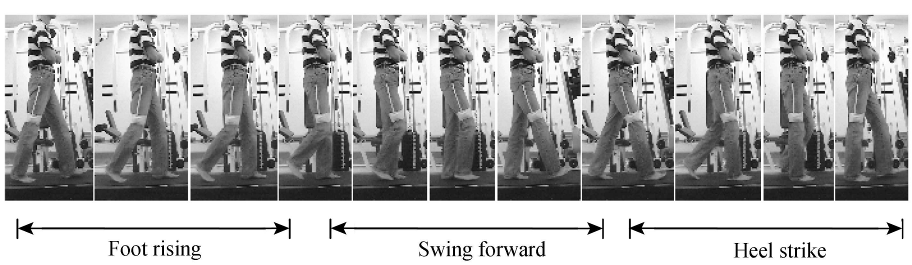


Fig. 4 The three phases of a gait cycle: foot rising, swing forward and heel strike

4 Estimation of the thigh flexion angle

The thigh flexion angle cannot be computed directly from the measurements of the accelerometers.

Besides gravitational field and body posture, the accelerations due to the body movement are also included in the measurements. In the mathematical model of a gait cycle, each of the three factors mentioned above plays a role and interacts with one another. In this paper, Kalman filter is applied to make minimum mean square error (MMSE) estimates to the parameters that are caused by these factors.

The relationship between the flexion angles of the lower limb segments and joint angles is revealed by Fig. 5(a). It is seen that the thigh flexion angle ϕ and the shank flexion angle ϕ are closely associated with the hip angle α and knee angle β. In the accelerometer coordinates depicted in Fig. 5(b), thigh flexion angle, denoted as θ, is defined as the angle between the thigh and vertical direction. Besides θ, angular velocity, $v = d\theta/dt$, is also an important factor for describing the movement of the thigh during gait cycles. The definitions of the other system variables are given in Fig. 5(b). Note that a and c are vertical and horizontal accelerations with respect to the ground coordinates while b and d are y and x accelerations with respect to the accelerometer coordinates.

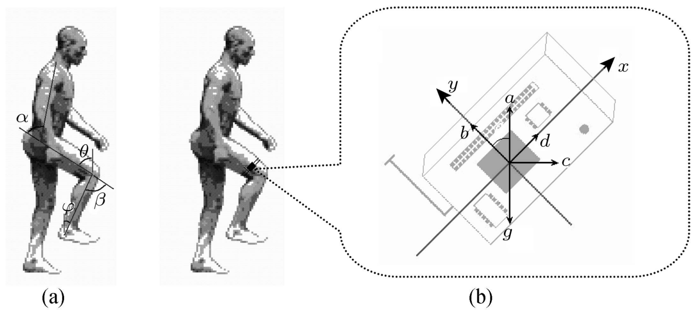


Fig. 5 (a) Relationship between flexion angles of the lower limb and joint angles: α - hip angle, β - knee angle, θ - thigh flexion angle, ϕ - shank flexion angle. (b) Variables and measurements of the accelerometer: a - vertical acceleration, c - horizontal acceleration, b - y-acceleration, d - x-acceleration

The system model of the movement of the thigh during gait cycles is thus determined by the four variables (θ, v, a and c) mentioned above. b and d are measurements of the accelerometer.

4.1 System model

The swing of the thigh is modeled by constant angular velocity model. In another word, the angular speed is assumed changing little within short period. The state update function of the system is written as in (1).

$$\begin{bmatrix} \theta_k \\ v_k \\ a_k \\ c_k \end{bmatrix} = \begin{bmatrix} 1 & t_s & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} \theta_{k-1} \\ v_{k-1} \\ a_{k-1} \\ c_{k-1} \end{bmatrix} + \begin{bmatrix} w_\theta \\ w_v \\ w_a \\ w_c \end{bmatrix} \tag{1}$$

where the subscript $k-1$ indicates time $k-1$ while k indicates time k, and t_s is the sampling interval. w_θ, w_v, w_a, w_c represent system noise. They are assumed to be independent, zero mean Gaussian noise with distribution function given below

$$P(w_\theta, w_v, w_a, w_c) \sim N(0, Q) \tag{2}$$

where $Q = \begin{bmatrix} Q_\theta & 0 & 0 & 0 \\ 0 & Q_v & 0 & 0 \\ 0 & 0 & Q_a & 0 \\ 0 & 0 & 0 & Q_c \end{bmatrix}$ is the covariance matrix. Q_θ, Q_v, Q_a, and Q_c are variance of the state variables, respectively.

The state transition matrix, matrix A, is derived from (1). Mathematically,

$$A = \begin{bmatrix} 1 & t_s & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{3}$$

The measurement functions of the system are given as follows.

$$\begin{cases} d_k = -g\sin\theta_k - a_k\cos\theta_k + c_k\sin\theta_k + w_d \\ b_k = -g\cos\theta_k + a_k\sin\theta_k + c_k\cos\theta_k - rv_k^2 + w_b \end{cases} \tag{4}$$

where w_x and w_y are measurement noise, r is the distance between the hip joint and the accelerometer. They are also of independent, zero-mean Gaussian distribution, *i.e.*

$$P(w_d, w_b) \sim N(0, R) \tag{5}$$

where $R = \begin{bmatrix} R_d & 0 \\ 0 & R_b \end{bmatrix}$ is the covariance matrix. R_d and R_b are variance of the measurements.

(4) can also be written in matrix form as follows.

$$\begin{bmatrix} d_k \\ b_k \end{bmatrix} = h(\theta_k, v_k, a_k, c_k) + \begin{bmatrix} w_d \\ w_c \end{bmatrix} \tag{6}$$

The relationship between the measurements (b and d), thigh flexion angle (θ), angular velocity (v) and accelerations (a and c) is non-linear. To use Kalman filter to analyze such a system, local linearization should be carried out.

By differentiating h with respect to the state variables, *i.e.* $H = \frac{\partial h}{\partial(\theta_k, v_k, a_k, c_k)}$, we have

$$H = \begin{bmatrix} -g\cos\theta_k + a_k\sin\theta_k + c_k\cos\theta_k & 0 & -\cos\theta_k & \sin\theta_k \\ g\sin\theta_k + a_k\cos\theta_k - c_k\sin\theta_k & -2rv_k & \sin\theta_k & \cos\theta_k \end{bmatrix} \tag{7}$$

Local linearization is then implemented as follows.

$$\begin{bmatrix} d_k \\ b_k \end{bmatrix} = \begin{bmatrix} \tilde{d}_k \\ \tilde{b}_k \end{bmatrix} + H \cdot \begin{bmatrix} \theta_k - \tilde{\theta}_k \\ v_k - \tilde{v}_k \\ a_k - \tilde{a}_k \\ c_k - \tilde{c}_k \end{bmatrix} + \begin{bmatrix} w_d \\ w_c \end{bmatrix} \tag{8}$$

where $\tilde{d}_k$ and $\tilde{b}_k$ are the approximations of d_k and b_k, $\tilde{\theta}_k$, $\tilde{v}_k$, $\tilde{a}_k$, and $\tilde{c}_k$ are estimates of θ_k, v_k, a_k, and c_k, respectively.

In addition to the state update and measurement functions mentioned above, the covariance matrix of the *a posteriori* estimates of the state variables is also an important component of the system model. The covariance matrix P_k is defined in (9).

$$P_k = \begin{bmatrix} P_\theta & 0 & 0 & 0 \\ 0 & P_v & 0 & 0 \\ 0 & 0 & P_a & 0 \\ 0 & 0 & 0 & P_c \end{bmatrix} = E\left\{ \begin{bmatrix} \theta_k - \tilde{\theta}_k \\ v_k - \tilde{v}_k \\ a_k - \tilde{a}_k \\ c_k - \tilde{c}_k \end{bmatrix} \cdot [\theta_k - \tilde{\theta}_k v_k - \tilde{v}_k a_k - \tilde{a}_k c_k - \tilde{c}_k] \right\} \tag{9}$$

Because the four state variables are assumed independent to one another, matrix P_k is diagonal.

4.2 Initialization

The initial configuration of the state variables and covariance matrix P_0 is based on the initial body status. In this system, it is assumed that at time $t = 0$, the body status is the foot rising phase of a gait cycle. A set of empirical values are then given in Table 1. Although these values may not well reveal body status at time $t = 0$, the difference between the estimated values and true values decreases as the Kalman recursion goes on. In addition to the state variables and covariance matrix, the co-variances of the system noise Q and measurement noise R are also listed in Table 1. Note that these parameters are constant stimuli and do not change over time.

Table 1 Initial settings of the Kalman filter

	Initial values			
State variables	$\theta_0 = -0.3rad$	$v_0 = 0rad/s$	$a_0 = 1m/s^2$	$c_0 = 0.2m/s^2$
Covariance matrix P_0	$P_\theta = 0.5rad^2$	$P_v = 10(rad/s)^2$	$P_a = 10(rad/s^2)^2$	$P_c = 10(rad/s^2)^2$
System noise Q	$Q_\theta = 0.01rad^2$	$Q_v = 0.1(rad/s)^2$	$Q_a = 1(rad/s^2)^2$	$Q_c = 1(rad/s^2)^2$
Measurement noise R	$R_d = 4(rad/s^2)^2$	$R_b = 4(rad/s^2)^2$		

4.3 Prediction

Using the system model mentioned above, at time k, the *a priori* estimates of the state variables are computed as follows,

$$\begin{bmatrix} \theta_{(k|k-1)} \\ v_{(k|k-1)} \\ a_{(k|k-1)} \\ c_{(k|k-1)} \end{bmatrix} = \begin{bmatrix} 1 & t_s & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} \tilde{\theta}_{k-1} \\ \tilde{v}_{k-1} \\ \tilde{a}_{k-1} \\ \tilde{c}_{k-1} \end{bmatrix} \tag{10}$$

where the subscript $(k|k-1)$ indicates the *a priori* estimates of the state variables, $\tilde{\theta}_{k-1}$, $\tilde{v}_{k-1}$, $\tilde{a}_{k-1}$ and $\tilde{c}_{k-1}$ are a posteriori estimates of the state variables at time $t-1$.

The a priori estimate of the covariance matrix P at time k is estimated *via* (11)

$$P_{(k|k-1)} = A\tilde{P}_{(k-1)}A^T + Q \tag{11}$$

where the subscript $(k|k-1)$ has the same meaning as in (10) and $\tilde{P}_{(k-1)}$ denotes the *a posteriori* estimate of matrix P at time $k-1$.

The one-step predictions, or *a priori* estimates of the measurements are given by,

$$\begin{cases} d_{(k|k-1)} = -g\sin\theta_{(k|k-1)} - a_{(k|k-1)}\cos\theta_{(k|k-1)} + c_{(k|k-1)}\sin\theta_{(k|k-1)} \\ b_{(k|k-1)} = -g\cos\theta_{(k|k-1)} + a_{(k|k-1)}\sin\theta_{(k|k-1)} + c_{(k|k-1)}\cos\theta_{(k|k-1)} - rv^2_{(k|k-1)} \end{cases} \tag{12}$$

4.4 Measurement update

At time k, the Kalman gain is computed using (13).

$$K_k = P_{(k|k-1)}H^T(HP_{(k|k-1)}H^T + R)^{-1} \tag{13}$$

And the a posteriori estimates of the state variables are given by (14),

$$\begin{bmatrix} \tilde{\theta}_k \\ \tilde{v}_k \\ \tilde{a}_k \\ \tilde{c}_k \end{bmatrix} = \begin{bmatrix} \theta_{(k|k-1)} \\ v_{(k|k-1)} \\ a_{(k|k-1)} \\ c_{(k|k-1)} \end{bmatrix} + K_k \cdot \begin{bmatrix} d_k - d_{(k|k-1)} \\ b_k - b_{(k|k-1)} \end{bmatrix} \tag{14}$$

where d_k and b_k are the sensor readings at time k. The entries $d_k - d_{(k|k-1)}$ and $b_k - b_{(k|k-1)}$ are commonly referred to as measurement innovation or the residual.

The error covariance matrix P_k is updated as follows,

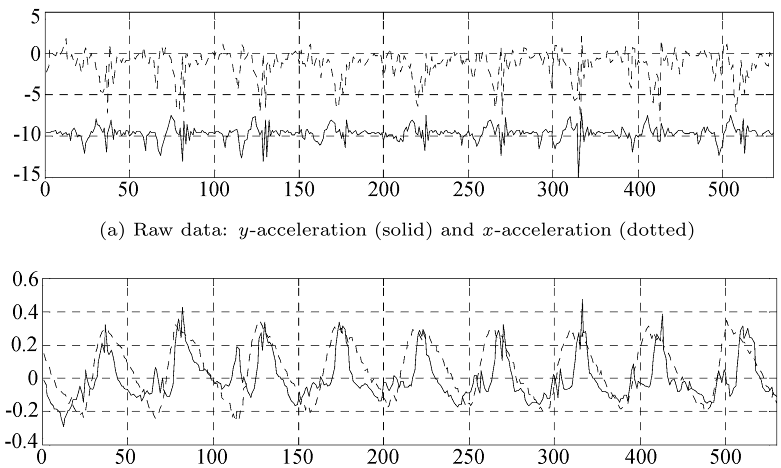
$$\tilde{P}_k = [1 - K_kH]P_{(k|k-1)} \tag{15}$$

The steps mentioned in Section 4.3 and 4.4 are repeated at each time slot and the values of the state variables are estimated.

5 Experiments

Experiments are conducted to assess the performance of the proposed Kalman filter. The experiment scenario is depicted in Fig. 4 where the subject is asked to walk along a treadmill at the speed of 2km/h, 3km/h, and 4km/h, respectively. To evaluate the accuracy of the KF, markers are also fixed at the exterior sides of both thighs as illustrated in Figs. 2(a) and 4. While the subject is walking, accelerations are measured by the accelerometers and video is made as well.

The video of walking is segmented into frames as depicted in Fig. 4. For these frames, the thigh flexion angle is defined as the angle between the marker and vertical direction, whose value is manually measured from the image. At the speed of 2km/h, the waveforms of the flexion angle estimated using the KF and measured from video are depicted in Fig. 6. It is seen that the estimated angle demonstrates same fluctuation as that measured from the video. The same experiment is conducted on other three subjects of different height. Statistics show that the estimation error is within $\pm 0.07rad$ at the speed of 2km/h, $\pm 0.08rad$ at 3km/h, and $\pm 0.11rad$ at 4km/h, respectively. Estimation error shows the trend of increase as the walking speed increases. This phenomenon is explained as follows: At a higher walking speed, the muscle force is greater than that of a lower speed. Thus the accelerations measured by the accelerometers are bigger and change more drastically. The KF, by its very nature a low-pass filter, may not react fast enough for such changes and thus the estimation error increases.



(a) Raw data: y-acceleration (solid) and x-acceleration (dotted)

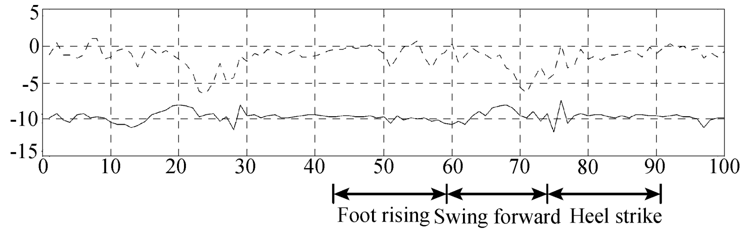
(b) Thigh flexion angle estimated using the KF (solid) and measured from video (dotted)

Fig. 6 Comparison between the KF and video-based approach

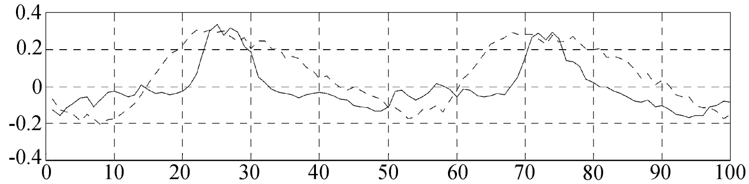
The waveforms depicted in Fig. 6 consist of several gait cycles. A more detailed study about the thigh-related features during one gait cycle is carried out in Fig. 7. It is seen that during the foot rising and swing forward phases, the thigh flexion angle increases from 0 to about 0.3rad ($\approx 18^{\circ}$) and the angular velocity also increases. It indicates that the muscle drives the thigh to swing forward. Once the maximum value is reached, the flexion angle decreases because the foot contacts ground and the trunk moves forward, which signifies the beginning of the heel strike phase. If the hip joint is assumed stable, the thigh is swinging backward. Thus the angular velocity decreases and becomes negative during this interval. At the moment that the other foot contacts ground, the thigh flexion angle reaches the minimum value and the foot rising phase of a new gait cycle is pending. In this way, the foot rising, swing forward and heel strike phases repeat for each gait cycle.

During the heel strike phase, the angular velocity decreases from a positive value to a negative value. In Fig. 7(c), a zero-cross point on the waveform of angular velocity is observed and highlighted which corresponds to the moment of foot contact. This feature is more robust than the gait segmentation approach based on vertical acceleration[2,8] because a zero cross point is more easily detected than a local minimum point on the waveform of vertical acceleration. As a result, the angular velocity of the swing of the thigh can be applied for gait cycle segmentation.

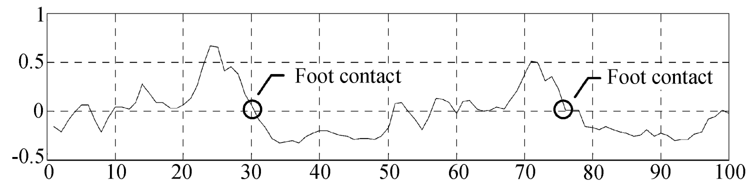
The trace of the covariance matrix ($P_\theta + P_v + P_a + P_c$) in the recursion is depicted in Fig. 7(d). The value of the trace is bigger during the heel strike phase but smaller during the foot rising and swing forward phases. The reason underlying this phenomenon is that the accelerations in the heel strike phase change more violently than that in the foot rising and swing forward phases (see Fig. 7(a)). Although there are fluctuations in the waveform depicted in Fig. 7(d), the trace will not diverge and is comparably stable during the course of Kalman recursion. It indicates that the proposed Kalman filter is capable of tracking the thigh flexion angle and the angular velocity during the gait cycles.



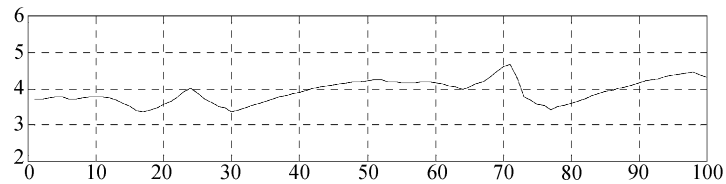
(a) Raw data: y-acceleration (solid) and x-acceleration (dotted)



(b) Thigh flexion angle estimated using the KF (solid) and measured from video (dotted)



(c) Waveform of the angular velocity and the foot contact point



(d) Waveform of the trace of the covariance matrix

Fig. 7 Parameters of the KF during the recursion

6 Conclusion

The Kalman filter proposed in this paper is specially tailored to track the change of thigh flexion angle during gait cycles. Experimental results indicate that the estimated parameters may well reveal the temporal features of gait cycles. The proposed approach is based on simple hardware design: one biaxial accelerometer attached at one thigh. It thus proves that gait analysis for ambulatory subject, especially those do not have stringent requirement on accuracy, can be made possible using Kalman filter and biaxial wearable accelerometers.

References

1 Oberg T, Karsznia A, Oberg K. Joint angle parameters in gait: Reference data for normal subjects, 10-79 years of age. *Journal of Rehabilitation Research and Development*, 1994, **31**(3): 199∼213

2 Zijlstra W, Hof At L. Assessment of spatio-temporal gait parameters from trunk accelerations during human walking. *Gait Posture*, 2003, **18**(2): 1∼10

3 Pataky Z, Faravel L, Silva J D, Assal J P. A new ambulatory foot pressure device for patients with sensory impairment. A system for continuous measurement of plantar pressure and a feed-back alarm. *Journal of Biomechanics*, 2000, **33**(9): 1135∼1138

4 Menz H B, Lord S R, Fitzpatrick R C. Acceleration patterns of the head and pelvis when walking on level and irregular surfaces. *Gait Posture*, 2003, **18**(2): 35∼46

5 Salarian A, Russmann H, Vingerhoets F J, Dehollain C, Blanc Y, Burkhard P R, Aminian K. Gait assessment in Parkinson's disease: Toward an ambulatory system for long-term monitoring. *IEEE Transactions on Bio-medical Engineering*, 2004, **51**(8): 1434∼1443

6 Willemsen A Th M, Bloemhof F, Boom H B K. Automatic stance-swing phase detection from accelerometer data for peroneal nerve stimulation. *IEEE Transactions on Bio-medical Engineering*, 1990, **37**(12): 1201∼1208

7 Sabatini A M, Martelloni C, Scapellato S, Cavallo F. Assessment of walking features from foot inertial sensing. *IEEE Transactions on Bio-medical Engineering*, 2005, **52**(3): 486∼494

8 Li H Q, Wu J K, Bao X M, Cheng D L, Dong L. Real-time activity monitoring using wireless wearable sensors. In: Proceedings of International Conference on Pervasive Systems and Computing. Las Vegas, USA, 2005

9 Luinge H J, Veltink P H. Inclination measurement of human movement using a 3-D accelerometer with autocalibration. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 2004, **12**(1): 112∼121

10 Najafi B, Aminian K, Paraschiv-Ionescu A, Loew F, Bula C J, Robert P. Ambulatory system for human motion analysis using a kinematic sensor: Monitoring of daily physical activity in the elderly. *IEEE Transactions on Bio-medical Engineering*, 2003, **50**(6): 711∼723

11 [Online], available: http://www.frontiernet.net/ imaging/gait_model.html, Jan. 11, 2006

12 [Online], available: http://www.xbow.com/Products/productsdetails.aspx?sid=75, Mar. 20. 2006

13 Dong L, Wu J K, Bao X M, Li H Q, Cheng D L. Tracking of body status using extended Kalman filter. *International Workshop on Nonlinear Signal and Image Processing*. Japan, 2005

DONG Liang Received his Ph. D. degree from National University of Singapore in 2005. Currently, he is a research fellow in the Institute for Infocomm Research, Singapore. His research interests include speech recognition, signal processing, and sensor networks.

WU Jian-Kang Principal scientist of the Institute for Infocomm Research, the national research institute of Singapore. He is now professor in the Graduate School, Chinese Academy of Sciences, and the director of the Sensor Networks and Applications Research Center, a joint research organization between the Institute of Automation and the Graduate School, Chinese Academy of Sciences. His research interests include sensor networks, digital media processing, communication and right management, and imaging systems.

BAO Xiao-Ming Received his bachelor, master, and Ph. D. degrees at Department of Automatic Control of Shanghai Jiaotong University in 1984, 1987, and 1991, respectively. He is currently a research staff at Institute for Infocomm Research in Singapore. His research interests include real-time embedded system design and implementation, wireless body sensor network, and multi-modal sensor data fusion for personalized healthcare applications.

XIAO Wen-Dong Received his Ph. D. degree from the Northeastern University, China in 1995. Currently he is a senior research fellow in the Institute for Infocomm Research, Singapore. His research interests include distributed estimation and data fusion, sensor management, Quality of Service (QoS) provisioning, networking protocols, and cross-layer integration in wireless *ad hoc* & sensor networks.