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Ambulatory Monitoring of Human Posture and Walking Speed Using Wearable Accelerometer Sensors

Wee-Soon, Yeoh, Isaac Pek, Yi-Han Yong, Xiang Chen, and Agustinus Borgy Waluyo
Institute for Infocomm Research, A*STAR, Singapore
Email: {wsyeoh,ipek,yhyong, xchen, awaluyo}@i2r.a-star.edu.sg

Abstract—**This paper describes a new classification system for real-time monitoring of physical activity, which is able to detect body postures (lying, sitting, and standing) and walking speed with data acquired from three wearable biaxial accelerometer sensors deployed in a wireless *body sensor network*. One sensor is waist-mounted while the remaining two are attached to the respective thighs. Two studies were conducted for the evaluation of the system, with each study involving five human subjects. Results from the first study indicated an overall accuracy of 100% for classification of lying, sitting, standing, and walking across a series of 40 randomly chosen tasks. In our system, estimated walking speeds are used to distinguish between different types of movement activity (walking, jogging, and running), and the accuracy of its estimation was evaluated in our second study which gave an overall mean-square error (MSE) of 1.76 (km/h)^2.**

I. Introduction

THE progressive miniaturization of wearable sensor devices has made the use of such devices more acceptable to medical patients, and the adoption of wearable sensors for medical applications has become increasingly pervasive throughout the healthcare industry as a direct result.

The deployment of a number of wearable sensor devices in a wireless sensor network known as a *Body Sensor Network* (BSN) opens up many exciting opportunities for medical caregivers to monitor patients in real-time. Healthcare applications can continuously monitor a patient for an extended period of time; detecting potential life-threatening activities or situations, and relaying critical information to emergency services for rapid medical response to patients. These systems are particularly vital in monitoring patients with limited mobility, for example, the elderly, handicapped patients or patients undergoing rehabilitation.

In order to support the detection of such life-threatening activities, there arises a need for healthcare applications to incorporate an accurate motion classification algorithm. Given accurate knowledge of a patient's current activity, applications can then synergize this information with other physiological data to derive/facilitate a well-informed decision and/or a highly accurate diagnosis of the patient's current health condition.

The purpose of our work is to improve the decision-making process of real-time healthcare monitoring systems through accurate estimations of a patient's flexion angles derived from raw accelerometer sensor data, particularly in the domain of activity classification [1]–[3]. For this purpose, we have extended our previous work, which utilizes a dynamic filtering technique [4] and adapted it for our current work. The results of our classification system are promising and exhibit a high degree of accuracy.

This paper is organized as follows. Section II presents the proposed classification for ambulatory monitoring. Section III contains our experimental results and an in-depth analysis of our results. Section IV comprises our conclusion and future work.

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II. Methods

This section presents our ruled-based Heuristic activity classification system that utilizes the *Extended Kalman* (EK) Filtering algorithm for tracking the flexion angles of the human body [4]. It comprises the *Postural* and *Movement Classifiers* for activity tracking, as depicted in Fig. 1.

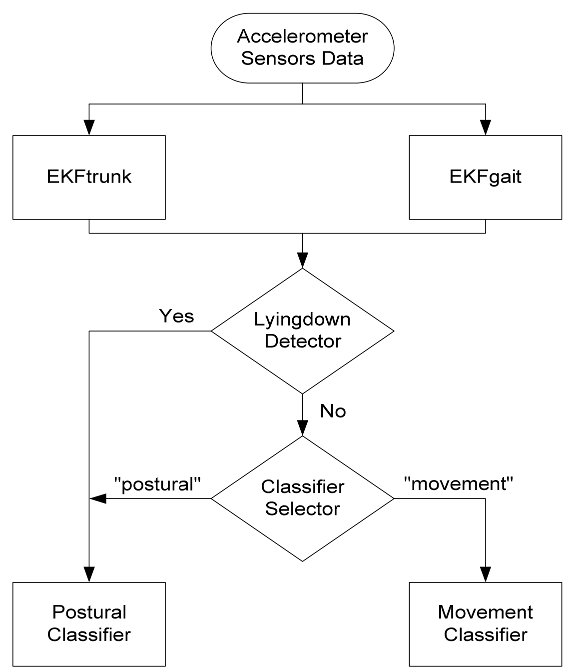

Fig. 1. Block diagram of the rule-based Heuristic system used for real-time activity classification. This flowchart displays the major components of the activity classification system.

As shown in Fig. 1, raw accelerometer sensor data are first processed by the EK filters (*EKFtrunk* and *EKFgait*) for the estimation of the trunk and thigh flexion angles respectively. These angles are subsequently utilized by the *Classifier Selector*, as well as the Postural and *Movement Classifiers*.

The *Lyingdown Detector* serves to give a quick indication of the lying down posture if the trunk sensor's vertical acceleration is less than 0.98 m/s^2 while the horizontal acceleration is greater than 8.82 m/s^2 or less than 0.98 m/s^2. The *Classifier Selector* may then be bypassed if the sensor wearer is indeed in the lying down posture.

A. EK Filtering Algorithm

The purpose of having the EK filter is to provide an accurate estimation of the flexion angles of the human body, and its detailed derivation is referred to in [4]. The filter is currently used as *EKFgait* and may also be used as *EKFtrunk* (by setting l to be of a shorter length). This filtering algorithm obtains the discrete-time dynamics by discretizing the continuous-time kinematic model that adopts the *Continuous Wiener Process Acceleration* (CWPA) *Model* where disturbances in the system dynamics are modeled as random inputs. In the CWPA model, motion of a constant angular acceleration object for the flexion angle θ is described by $\dddot{\theta}$, which is a continuous-time zero-mean white noise process that models acceleration changes.

Given the system state vector $\mathbf{x} = \begin{bmatrix} \theta & \dot{\theta} & \ddot{\theta} \end{bmatrix}^{\mathrm{T}}$, the time update of the state estimate and estimation-error covariance are as follows:

$$\begin{aligned} \hat{\mathbf{x}}_k^- &= \mathbf{A}\ \hat{\mathbf{x}}_{k-1}^+ \\ \mathbf{P}_k^- &= \mathbf{A}\ \mathbf{P}_{k-1}^+ \mathbf{A}^{\mathbf{T}} + \mathbf{Q} \end{aligned} \quad , \tag{1}$$

where $\mathbf{A}$ is the transition matrix and $\mathbf{Q}$ is the covariance matrix of the discrete-time process noise:

$$\mathbf{A} = \begin{bmatrix} 1 & T & \dfrac{T^2}{2} \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix}, \quad \mathbf{Q} = \begin{bmatrix} \dfrac{T^5}{20} & \dfrac{T^4}{8} & \dfrac{T^3}{6} \\ \dfrac{T^4}{8} & \dfrac{T^3}{3} & \dfrac{T^2}{2} \\ \dfrac{T^3}{6} & \dfrac{T^2}{2} & T \end{bmatrix} \underset{\sim}{q}, \tag{2}$$

where T is the sampling period and $\underset{\sim}{q}$ is the variance of the discrete-time zero-mean white noise process.

Fig. 2 illustrates the body dynamics that have been incorporated into the system model of the EK filter. Three acceleration components that describe this model are the gravitational acceleration, radial acceleration, and tangential acceleration.

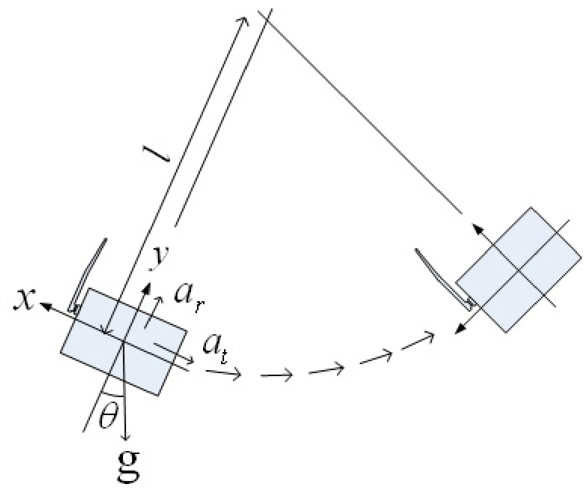

Fig. 2. An illustration of the variables definition associated with the system model.

Using this model and the variable definition as illustrated, the output measurement of the accelerometer sensor is given as follows:

$$\begin{aligned} &\text{y - reading}: \ y_k = a_{r,k} - \mathbf{g}\cos(\theta_k) + n_{y,k} \\ &\text{x - reading}: \ x_k = -a_{t,k} - \mathbf{g}\sin(\theta_k) + n_{x,k} \end{aligned} \quad , \tag{3}$$

where $\mathbf{g}$ is the earth gravity, $a_{r,k} = \dot{\theta}_k^2 l$ and $a_{t,k} = \ddot{\theta}_k l$ are the discrete-time measurements of the *tangential* and *radial* acceleration components respectively. The measurement noise $n_{y,k}$ and $n_{x,k}$ are additive, zero mean, white, and uncorrelated with the process noise. If (3) is rewritten as:

$$\mathbf{y}_k = \mathbf{h}_k\left(\theta_k, \dot{\theta}_k, \ddot{\theta}_k\right) + \mathbf{n}_k \ , \tag{4}$$

the measurement update, for the first-order EK filter, is derived based on a first order *Taylor* series expansion of the nonlinear measurement equations around $\mathbf{x}_k = \hat{\mathbf{x}}_k^-$ and the corresponding updated state error covariance are given as:

$$\begin{aligned} \hat{\mathbf{x}}_k^+ &= \hat{\mathbf{x}}_k^- + \mathbf{K}_k\left[\mathbf{y}_k - \mathbf{h}_k\left(\hat{\theta}_k^-, \hat{\dot{\theta}}_k^-, \hat{\ddot{\theta}}_k^-\right)\right] \\ \mathbf{P}_k^+ &= \left(\mathbf{I} - \mathbf{K}_k\mathbf{H}_k\right)\mathbf{P}_k^-\left(\mathbf{I} - \mathbf{K}_k\mathbf{H}_k\right)^T + \mathbf{R}_k \end{aligned} \quad , \tag{5}$$

where $\mathbf{R}_k$ is the covariance matrix of $\mathbf{n}_k$, and $\mathbf{K}_k$ is the EK filter gain:

$$\mathbf{K}_k = \mathbf{P}_k^-\ \mathbf{H}_k^T\left(\mathbf{H}_k\ \mathbf{P}_k^-\ \mathbf{H}_k^T + \mathbf{R}_k\right)^{-1}, \tag{6}$$

and $\mathbf{H}_k$ is the partial derivative matrix:

$$\mathbf{H}_k = \begin{bmatrix} \mathbf{g}\sin\left(\hat{\theta}_k^-\right) & 2\ \hat{\dot{\theta}}_k^-\ l & 0 \\ \text{-}\mathbf{g}\cos\left(\hat{\theta}_k^-\right) & 0 & -l \end{bmatrix}. \tag{7}$$

B. Classifier Selector

This classifier determines if the underlying physical activity belongs to either the "postural" or "movement" class, based on the state diagram illustrated in Fig. 3. In this figure, P and S denote the periodic and static gait activities respectively. The average value of the minimum and maximum flexion angles falling within the time duration of 0.5 s are denoted by $\theta_{m,l}$ and $\theta_{m,r}$ for both the left and right thighs respectively. m_T is the variance of the trunk sensor's vertical acceleration, and $P/!S$ denotes a state where the previous gait is non-static whereas the current gait is periodic. A periodic gait activity implies that both thighs are swinging in the opposite direction within the specified time duration.

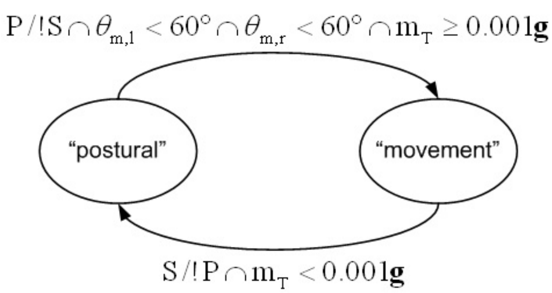

Fig. 3. Method for determining the type of physical activity performed by the sensors wearer.

C. Postural Classifier

The *Postural Classifier* decides if the underlying activity is of the *lying*, *sitting*, or *standing* postures, based on the set of trunk (θ_{tr}), left thigh (θ_l), and right thigh (θ_r) flexion angles. For *lying* posture classification, all angles are to fall within the range of 60° to 120°. For *sitting* posture, θ_{tr} is to fall within -15° and 55° while both thigh angles are to fall within 35° and 160°. As for the *standing* posture, all angles are to be within the specified range of -30° and 30°.

D. Movement Classifier

The *Movement Classifier* classifies the underlying activities as *walking*, *jogging*, and *running* movements if the estimated walking speed is less than 6.5 km/h, falls within 6.5 km/h and 9 km/h, and greater than 9 km/h respectively.

The estimation method is derived from the fact that force exerted by an object is directly proportional to the acceleration, and thus physical activity intensity will be a function of acceleration. With $a_{L,net}$ and $a_{R,net}$ representing the net acceleration of the left and right thighs, we define the *Average Net Acceleration* (ANA) as the time average obtained from the summation of $a_{L,net}$ and $a_{R,net}$ over a time duration of 2 s. Fig. 4 depicts a typical ANA histogram distribution of two walking speeds.

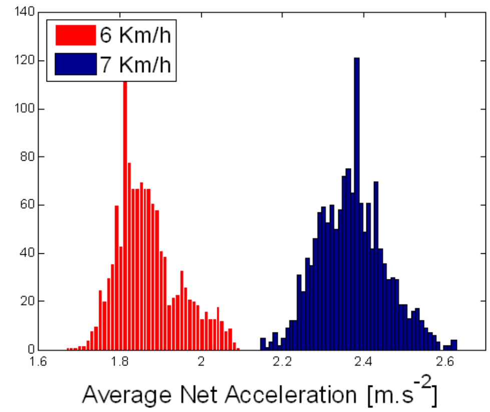

Fig. 4. ANA histograms plot of one of the test subjects walking on a treadmill at 6 km/h and 7 km/h.

The proposed walking speed estimator makes use of the least squares approach to fit the mean value of the ANA, x, to the third-order polynomial signal model. From this, we obtain the estimated walking speed $y = -0.1094 + 4.3871\,x - 0.9508\,x^2 + 0.1373\,x^3$, as illustrated in Fig. 5.

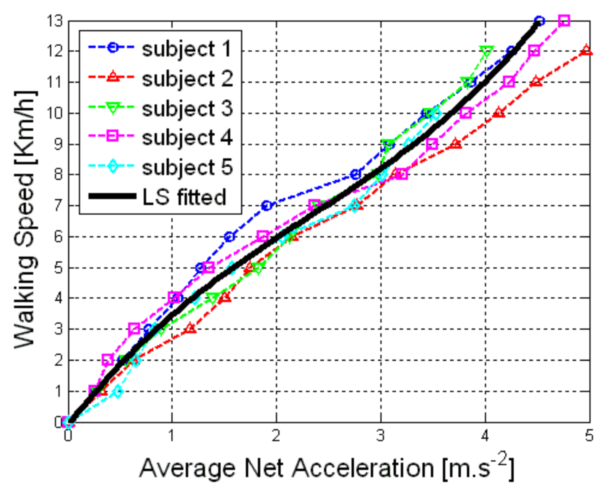

Fig. 5. Walking speed against the Net acceleration averaged over a time duration of 2 s for five test subjects. The bold line is the experimental data fitting by Least Squares (LS).

III. PRELIMINARY STUDY FOR AMBULATORY MONITORING

The setup for the ambulatory monitoring system is shown in Fig. 6. Three wearable wireless accelerometer sensors, comprising of a Crossbow MicaZ mote processor radio platform (MPR2400) and a Crossbow MicaZ biaxial accelerometer sensor board (MTS310CA), are attached to the trunk and both thighs of a human subject. The sampling rate for the accelerometer sensor is set to 25 Hz. A MicaZ node mated to a MIB510 serial interface board functions as a base-station for the BSN. Received data is aggregated and processed on a laptop via its RS-232 interface.

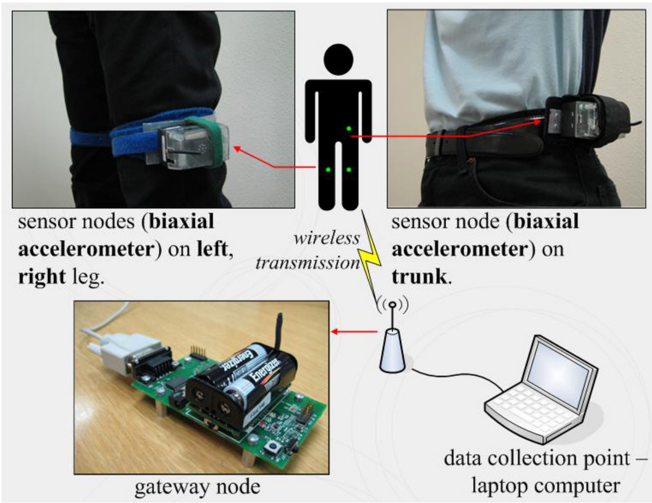

Fig. 6. An illustration of the system setup for ambulatory monitoring of human posture and walking speed.

Two studies were conducted with five test subjects. The first study consisted of a series of 40 tasks randomly selected by the evaluator from a set of lying, sitting, standing, and walking activities. Test subjects executed these activities accordingly, as shown in Fig. 7. Transitional activity is accepted if the activity is a logical transition between two activities, e.g., sitting is accepted as a transitional activity from lying to standing. No misclassification was detected throughout this study.

Fig. 7. Photo shots capture of the various activities for classification in the first study.

The second study is conducted on five test subjects running on a treadmill at speeds progressively increasing from 1 km/h to 13 km/h, depending on their physical fitness. The results of their estimated walking speeds are tabulated in TABLE I. The study gave an overall MSE of 1.76 $(km/h)^2$. The influence of a few bad samples with abnormally large values on the overall results, such as that shown by subject 4 at 3 km/h, is noteworthy. The MSE improved from 13.25 $(km/h)^2$ to 0.46 $(km/h)^2$ with the removal of these bad samples, resulting in a significant improvement in the overall MSE. The tabulated results show that the estimation accuracy degrades at speeds of higher than 10 km/h. This is likely due to the fact that at high speeds, accelerometers are functioning beyond their specification range of $\pm 2\,\mathbf{g}$.

TABLE I
RESULTS OF EXPERIMENTS DEMONSTRATING THE EFFECTIVENESS OF THE PROPOSED WALKING SPEED ESTIMATING TECHNIQUE. VALUES ARE GIVEN AS MSE IN $(km/h)^2$

Walking Speed (km/h)	Test subject					Overall MSE
	1	2	3	4	5	
1	0.04	0.16	0.01	0.09	0.68	0.20
2	0.03	0.20	0.03	0.36	0.56	0.23
3	0.06	1.04	0.06	13.25	0.09	2.79
4	0.16	0.93	0.60	0.25	0.03	0.35
5	0.65	0.26	0.36	0.34	0.09	0.35
6	1.19	0.16	0.08	0.14	0.11	0.33
7	1.56	0.56	0.05	0.08	0.46	0.49
8	0.20	0.51	0.14	0.78	0.08	0.34
9	0.38	1.42	0.38	0.28	0.08	0.54
10	0.60	2.60	0.43	0.33	0.26	0.86
11	0.29	5.39	0.57	0.85	-	1.99
12	0.14	10.18	1.38	0.77	-	2.94
13	0.32	2.59	-	1.32	-	1.33
Overall MSE	0.40	1.69	0.35	1.40	0.24	1.76

IV. CONCLUSION

We have presented a rule-based Heuristic system that can be used for real-time ambulatory monitoring, and delivers promising results. In future, our system can be extended to classify more complex activities such as climbing the stairs, going down the stairs and accidental falling.

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