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Recognition of Walking Behaviors for Pedestrian Navigation

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Abstract— **This paper presents a method for detecting and classifying walking behaviors based on acceleration measurements of a pedestrian, and is employed in an indoor navigation system currently being developed. The prototype navigation system uses a set of inexpensive and wearable sensors: a bi-axial accelerometer, a digital compass, and an infrared light detector. Using the measured acceleration data, the proposed method can detect forward steps and classify the steps as: "level ground," "up," and "down". The objective of the detection is to count steps for estimating the current position by dead-reckoning using heading measurements. The capability in detecting "up/down" steps can be used to correct estimated position errors. The effectiveness of the proposed method is demonstrated by experiments on six persons.**

Keywords—**activity-recognition, acceleration, walking, navigation, wearable computing**

I. Introduction

The ability to find the location of a user is one of the most important components of contextual sensing for many applications of wearable computing. If the application field is outdoors, then a Global Positioning System (GPS) may be a tremendously powerful tool for this task. In indoor situations, however, GPS is unavailable, and so many researcher have attempted to develop a variety of systems, sensors, and techniques to find the location of a user.

The most widely used systems may be infrared based beacon systems [1], [2]. This approach yields a high reliability, but is expensive in terms of installation and maintenance. Another approach is the use of a camera and natural or artificial landmarks. If artificial landmarks such as bar codes are stuck on a certain place, the vision-based system can estimate the user location by recognizing the landmarks. The natural landmark are those objects or feature that are already in the environment. Therefore, many learning-based location detection methods can be included in this category. Aoki *et al.* [3] developed a positioning system that uses a forward looking hat-mounted camera and a dynamic programming algorithm on a stand-alone PC. Clarkson *et al.* [4] suggested a similar system that uses a wearable camera and HMM algorithm to recognize a spatially-based user's situation. Unlike the above systems which identify discrete events, a system that uses an omni-directional camera and a probabilistic algorithm to track the location of a user has also been proposed in [5].

Instead of a vision system, Golding *et al.* [6] used a set of wearable sensors: accelerometer, magnetometer, light detector and temperature sensors, to recognize the location of a user. In our work [7], we suggested a hybrid method to track the location of a user continuously. The proposed method employs a hybrid position measurement method: dead-reckoning for relative measurements and an infrared-based beacon method for absolute measurements. To measure the incremental motion of a user, we focused on recognizing a motor activity, i.e., walking.

Some interesting works have also been done specifically on activity-recognition including walking: Ashbrook [8] presented a basic idea about the usability of walking detection for context awareness using an one-hand keyboard called "Twiddler". Recognition methods using accelerometers capable of distinguishing various activities of a user (sitting, standing, walking, ascending/descending, etc.) were proposed in [9].

In this paper, we describe a recognition method of the walking behaviors of a user using a few wearable sensors and a simple algorithm, which is one of the key function blocks of location recognition system. The proposed method can recognize not only walking behaviors, but also count the number of steps. An analysis on the acceleration profile is performed to find features for detecting forward steps reliably. We also show the relationship between the step size and walking speed. When the system detects a new step, it then tries to classify the step into one of three behaviors: walking on level ground ("level"), going up ("up") a stairway, or going down ("down") a stairway.

For the classification, we propose a method based on the distance comparison of current feature values and cross-correlation characteristics. Such recognition is important because it can be used as absolute position information (i.e., the starting place on a stairway), enabling the system to correct position errors. As is well known, dead-reckoning based location finding method can lead to accumulation errors, which increase proportionally to the distance traveled by the user. To correct such errors, the location recognition system uses an infrared light detector capable of detecting signals from a transmitter fixed at a certain place. The capability of stairway detection may be helpful for correcting such errors as well as for expanding the tracking performance to multi-story environments. We demonstrated the performance of the walking behavior recognition by experiments on six persons.

II. System Description

The system consists of a notebook PC (Intel Pentium II, 266 MHz), a card type data acquisition module, and a sensing module. The data acquisition module has 12-bit resolution, 16 single-ended analog input ports, eight digital I/O lines, and two 24-bit counter/timer units (DAQCard-AI-16E-4 from National Instruments Co.). The body-worn sensing module consists of a bi-axial accelerometer (ADXL 202EB from Analog Devices Inc.), a digital compass module (HMR-3000 from Honeywell) and an infrared light detector (IS486 from Sharp Co.).

The implemented sensing module is small and light, and is assumed to be fixed to the middle of the waist of the user, as shown in Figure 1. The reason for the selection of this position is to measure the forward and upward accelerations and heading accurately. In addition, comfort and unobstructed wearability are provided on the belt as evidenced by other mobile devices (e.g., cellular phones and pedometers).

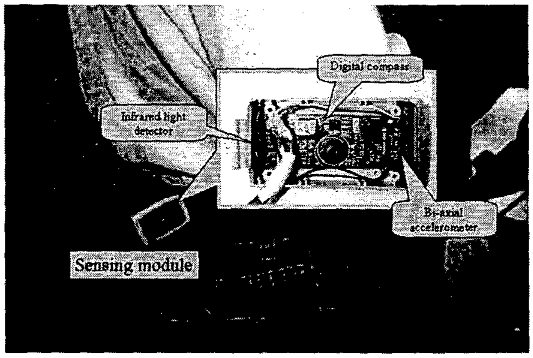

Fig. 1. Use and inside view of sensing module

The accelerometer measures the user's forward and upward accelerations, which are denoted by $\ddot{x}_o(t)$ and $\ddot{z}_o(t)$, respectively. The ac components are calculated by subtracting the average of 50 samples from each sampled data, then, the data is smoothed by a second-order elliptic digital filter with a 5 [Hz] cut-off frequency. This elimination of the dc components is to prevent drift errors derived from the movements of the sensing module, since the accelerometer can be affected by static accelerations such as the gravitational force. The data is read every 20 [msec], i.e., the sampling frequency is 50 [Hz]. The digital compass module can give us compass heading and roll, pitch information of the module via RS-232 serial communication channel.

The navigation system requires a calibration process to determine the important walk feature-normal walk speed and one step size. Accordingly, when the user walks in a predefined region at his/her normal speed, the system extracts the feature values to be used in the walking detection and classification, and calculates the average step size by counting steps with *a priori* known distances.

In normal operation phase, it is assumed that the system knows the user's starting location and heading, then the system estimates the current location by accumulating the incremental displacements-the unit of the displacement is one step. Thus, when a step is detected, the system calculate the new location to add the forward and right components of the displacements to the previous location.

III. STEP RECOGNITION

A. Walking behaviors

In ergonomics [10], one cycle of human walking (called the "gait cycle") is generally defined in terms of an interval of *time* during which one sequence of regularly recurring succession of *events* is completed. These sequential events are as follows: foot strike, opposite toe-off, opposite foot strike, and toe-off. Instead of a whole gait cycle, we consider a half gait cycle including only one foot strike, since it is easier to detect the foot strike on an acceleration measuring based system.

Figure 2 shows the typical trajectories of two pre-processed accelerations when a user walks on level ground. The positive values of $\ddot{x}(t)$ and $\ddot{z}(t)$ represent the forward and upward accelerations of the user, respectively. From the figure, we can easily find the half gait cycle of the user.

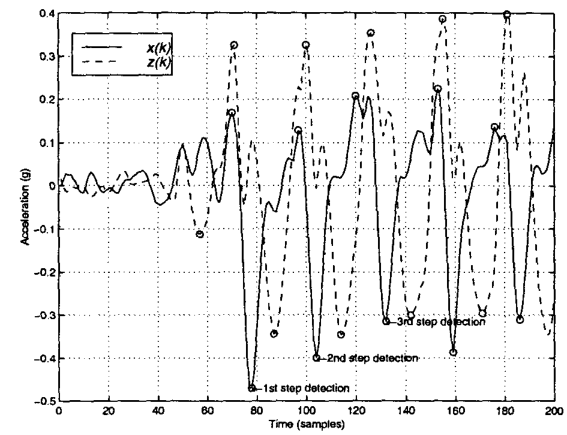

Fig. 2. Typical acceleration profiles of level ground walking: solid line $\ddot{x}(t)$ and dashed line $\ddot{z}(t)$

In order to find the relationship between the step size and walking speed, we measured these features from nine persons in walking experiments. Each person walked the same distance at three speeds: slow, normal, and fast. From our measurements, we found that if a user walks faster, both the step size and step rate [steps/sec] increase. We, therefore, introduced the ratio of the step size, and the rate for slow and fast walking with respect to normal walking to build our general model. Figure 3 shows the relationship between the ratio of the step size and ratio of the step rate from the data set. The total averages of the ratios of the step size ($\bar{k}_{d,j}$) and step rate($\bar{k}_{f,j}$) are computed as:

$$\bar{k}_{d,j} = \frac{1}{N}\sum_{i=1}^{N}(\bar{d}_j^i/\bar{d}_n^i),\ N = 9$$

$$\bar{k}_{f,j} = \frac{1}{N}\sum_{i=1}^{N}(\bar{f}_j^i/\bar{f}_n^i),\ j = \{s, f\}$$

where $\bar{d}_j^i$ and $\bar{f}_j^i$ represent the average of one step size and the step rate of the i-th person for slow or fast walking ($j = s, f$). This shows that the relationship is almost linear, accordingly, it can be simply modeled as a first- or second-order polynomial equation. In the next section, we describe a dynamic step size estimation method using a second-order polynomial model.

B. Step detection

Counting steps using a detection method allows the direct determination of the distance. Therefore, we need to find an accu-

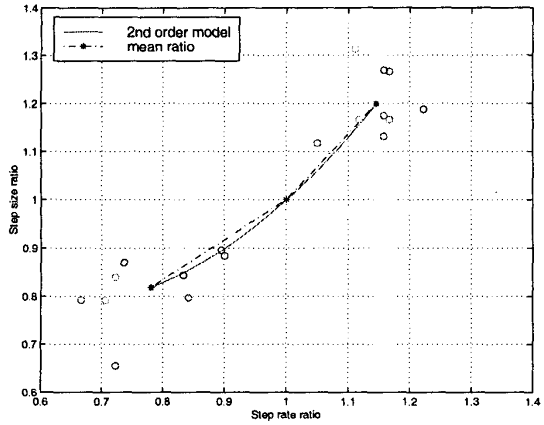

Fig. 3. Relationship between the step size and step rate

rate and robust detection method accommodating real-time processing. The following values are used as a basic feature vector.

$$\vec{a}(t) = \{\ddot{x}^{-}_{peak}(t_1), \ddot{x}^{+}_{peak}(t_2), \ddot{z}^{-}_{peak}(t_3), \ddot{z}^{+}_{peak}(t_4)\} \quad (1)$$

where $\ddot{x}^{(+,-)}_{peak}(t_{(1,2)})$ denotes a positive or negative peak value of the forward acceleration which is detected in the period from the moment of last step detection to current step detection, such as shown in Figure 2 with the mark $\circ$. The detection of these values can allow us to recognize the half one-step process.

In order to detect the feature values, we introduce a sliding window that keeps the past 25 data samples of $\ddot{x}$ and $\ddot{z}$. By using a conventional peak detection algorithm, the system tries to find the peak values at every sampling. When all four peaks are found, the system tests the following conditions to determine each new step.

1. Whether the absolute value of the four peaks are above the minimum threshold values, i.e., the i-th elements of the feature vector, i.e.,

$$|a_i(t)| > a_i^{Th},\ i = 1, \cdots, 4.$$

2. Whether the time since the last walking detection is greater than some minimum period, i.e., whether the maximum step rate is limited.

3. To prevent false detection from other body movements such as a standing walk, we introduce a lag parameter on the autocorrelation function of $\ddot{z}(t)$ as:

$$j_{zz,min} \equiv \min_{j=0,\cdots,49}\left[\sum_{n=0}^{49} \ddot{z}(n)\ddot{z}(n-j)\right] \quad (2)$$

The magnitude of the lag $j_{zz,min}$ must be greater than a threshold value.

If the above conditions are true, then the system increases the step count, and performs the dynamic step size estimation.

To estimate the current step size , we use a second-order polynomial model derived from the relationship shown by the following equation (shown also as the solid line in Figure 3).

$$\begin{aligned} k_d(t) &= 1.5k_f(t)^2 - 1.8475k_f(t) + 1.3468 \\ k_f(t) &= f(t)/\bar{f}_n(t_0) \\ d(t) &= k_d(t) \cdot \bar{d}_n(t_0) \end{aligned} \quad (3)$$

where $d(t)$ and $f(t)$ are the current step size and step rate, and $\bar{f}_n(t_0)$ and $\bar{d}_n(t_0)$ are the averaged normal step rate and size obtained from the calibration phase, respectively. Here, the current step rate is calculated using the autocorrelation function of z-acceleration. Using this method, the step size is estimated dynamically based on the walking speed.

C. Classification

As discussed in Section I, the detection of stairways is important to compensate relative location errors. The proposed classification method is based on a comparison of distance of current feature vector $\vec{a}(t)$ from pre-determined center points $\vec{a}^i(t_0)$ in a feature space as:

$$\min_i \|\vec{a}(t) - \vec{a}^i(t_0)\|,\ i = \{s, n, f, u, d\} \quad (4)$$

where $\|\cdot\|$ is the Euclidean norm, and the index $i = \{s, n, f, u, d\}$ represents slow, normal, fast level ground walking, and going up a stairway, and going down a stairway. Although the slow, normal, and fast walking behaviors are considered as one "level" behaviors, separation is introduced to increase the recognition performance. The center points $\vec{a}^i(t_0)$ are computed with the average feature values of normal walking in the calibration phase, and the average ratio of each walking feature value for normal walking. Each element of the center points is calculated as:

$$a^i_j(t_0) = \bar{k}^i_{a,j}(t_0)a^n_j(t_0) \quad (5)$$

where $j = \{1, \cdots, 4\}$, $i = \{s, f, u, d\}$. Average ratio values from data on six persons are shown in Table I.

	$k_{a,1}(t_0)$	$k_{a,2}(t_0)$	$k_{a,3}(t_0)$	$k_{a,4}(t_0)$
slow	0.734	0.761	0.551	0.692
fast	1.279	1.232	1.670	1.363
up	0.705	0.757	1.112	1.211
down	0.819	0.881	1.710	1.814

TABLE I

AVERAGE RATIOS OF FOUR BEHAVIORS FOR NORMAL WALKING FROM DATA ON SIX PERSONS

Using the above method only, the classifier cannot well discriminate between the "level" and "up/down" behaviors. To increase the recognition ratio, we therefore introduced a cross-correlation function of $\ddot{x}(t)$ and $\ddot{z}(t)$ as another feature. Figure 4 shows typical cross-correlation trajectories between forward and upward accelerations of three behaviors at the time a step is detected. As we can see from Figure 4, the cross-correlation characteristic of "down" is very distinguishable from the others. From this finding, we define the lags on cross-correlation function $r_{xz}(j)$ as:

$$j_{xz,min} \equiv \min_{j=0,\cdots,49} r_{xz}(j),$$
$$j_{xz,max} \equiv \max_{j=3,\cdots,49} r_{xz}(j)$$
$$r_{xz}(j) \equiv \sum_{n=0}^{49} \ddot{x}(n)\ddot{z}(n-j). \quad (6)$$

If $j_{xz,min} < j_{xz,max}$ and $r_{xz}(j_{xz,min}) < r_{xz}^{Th}$, then the system recognizes the current step as a "down" behavior.

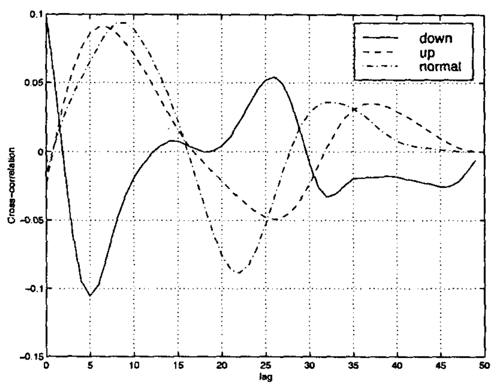

Fig. 4. Typical cross-correlation trajectories $r_{xz}(j)$ of "level," "up," and "down" behaviors

IV. Experimental Results

The walking data on six persons were used to evaluate the detection and classification method. The sampled data employed has 354 steps for "level" walking and 72 steps each for going "up" and "down" a stairway. Table II shows average results of the detection and classification method. As shown in Table II, the proposed method shows a satisfactory detection performance for the counting of steps. It is possible to increase the detection ratio with smaller threshold values, but we should note that there is a trade-off between sensitivity and noise immunity. The classification results also show a good performance for the "level" and "down" behaviors, but the "up" behavior it is not satisfactory.

Unit [%]	level	up	down	missing
level	96.3	1.4	0	2.3
up	38.9	54.2	0	6.9
down	2.8	0	95.8	1.4

TABLE II

Results of Detection and Classification Method

To solve this problem, we can consider utilizing personalized center points $\vec{a}^i$ for the user, since these values can be computed automatically from the navigation system. If infrared transmitters were installed at the starting points of stairways, then the system could extract the feature values of "up" and "down" behaviors for the user, and could make these values new center points. This means that the system could be adapted to each user while running. Results using this personalized center points are shown in Table III. The center points were computed from a half set of each person's data. We can see that the recognition ratio of "up" is increased from 54% to 83%.

Unit [%]	level	up	down	missing
level	96.3	1.7	0	2.0
up	11.1	83.3	0	5.6
down	0	2.8	95.8	1.4

TABLE III

Results of Detection and Classification Method Using Personalized Center Points

V. Conclusion and Future Work

In this paper, we proposed a walking behavior recognition method using simple accelerometers. The proposed recognition method not only to recognize user's walking behavior, but also to count steps like a pedometer. The proposed method is used as a basic function block of dead-reckoning based location recognition system in indoor environments. Experimental results showed a reliable performance for both step detection and classification.

To improve the performance of the step recognition, our future work includes adding different type of sensors, different positions on the body, and modifying the algorithm. Our aim is to implement a smaller and lighter prototype than the current one, and to also give the prototype a wireless connection capability to central mobile units (PDAs or laptop PCs) for more comfortable usage.

References

[1] T. Starner, D. Kirsch, and S. Assefa, "The locust swarm: An environmentally-powered, networkless location and messaging system," in *The First Int'l Symposium on Wearable Computers*, (Cambridge), pp. 169–170, October 1997.

[2] ELPAS Ltd., "EIRIS technology." (http://www.elpas.co.il/technology/index.html).

[3] H. Aoki, B. Schiele, and A. Pentland, "Realtime personal positioning systems for a wearable computers," in *The Third Int'l Symposium on Wearable Computers*, (San Francisco), pp. 37–43, October 1999.

[4] B. Clarkson, K. Mase, and A. Pentland, "Recognizing user context via wearable sensors," in *The Fourth Int'l Symposium on Wearable Computers*, (Atlanta, Georgia), pp. 69–75, October 2000.

[5] W. Rungsarityotin and T. E. Starner, "Finding location using omnidirectional video on a wearable computing platform," in *The Fourth Int'l Symposium on Wearable Computers*, (Atlanta, Georgia), pp. 61–68, October 2000.

[6] A. R. Golding and N. Lesh, "Indoor navigation system using a diverse set of cheap, wearable sensors," in *The Third Int'l Symposium on Wearable Computers*, (San Francisco), pp. 29–36, October 1999.

[7] S.-W. Lee and K. Mase, "A personal indoor navigation system using wearable sensors," in *The Second Int'l Symposium on Mixed Reality (ISMR01)*, (Yokohama, JAPAN), pp. 147–148, March 2001.

[8] D. Ashbrook, "Context sensing with the twiddler keyboard," in *The Third Int'l Symposium on Wearable Computers*, (San Francisco), pp. 197–198, October 1999.

[9] K. V. Laerhoven and O. Cakmakci, "What shall we teach our pants?," in *The Fourth Int'l Symposium on Wearable Computers*, (Atlanta, Georgia), pp. 77–83, October 2000.

[10] D. H. Sutherland, K. R. Ralston, and J. G. Gamble, *Human Walking*, ch. 2. Kinematics of Normal Human Walking, pp. 23–44. Williams & Wilkins, second ed., 1994.