Real-time Recognition of Daily Human Activities Using A Single Tri-axial Accelerometer

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Abstract

Recently human activity recognition using accelerometer has become a prominent research area in proactive computing. In this paper, we present a real-time activity recognition system using a single tri-axial accelerometer. Our system recognizes four primary daily human activities: namely walking, going upstairs, going downstairs, and sitting. The system also computes extra information from the recognized activities such as number of steps, energy expenditure, activity duration, etc. Finally, all generated information is stored in a database as daily log.

1. Introduction

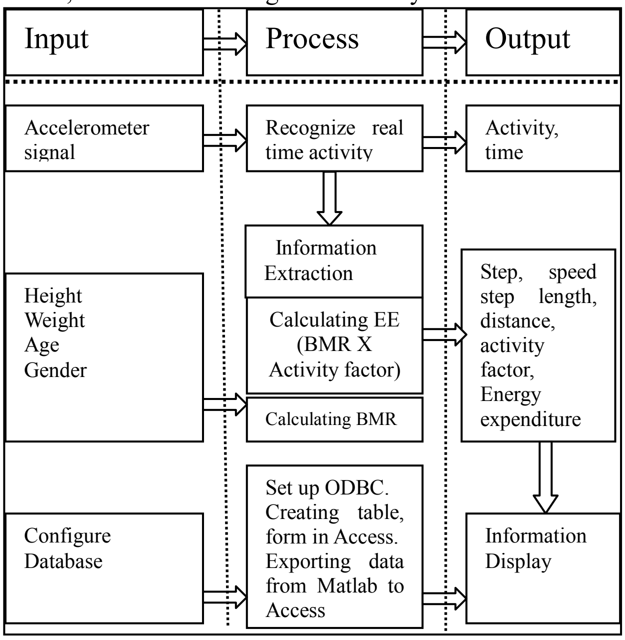
Lately tracking and recognition of daily human activities have become an important research field with numerous applications in many areas [1]: for instance, smart home healthcare systems for the aged [2, 3], real-time feedback of the activities via a body sensor network [4], and mobile phone medical care service [5]. Among these works, many works have been implemented using an accelerometer [6, 7] to recognize human activities, also yielding extra information such as energy expenditure [8].

In this work, we have developed a system that recognizes human activities in real-time and computes useful information such as number of steps, energy expenditure, activity duration, etc for the recognized activities. Our system also keeps this information in a database as daily log. From the database, we can extract and display the information of daily activities.

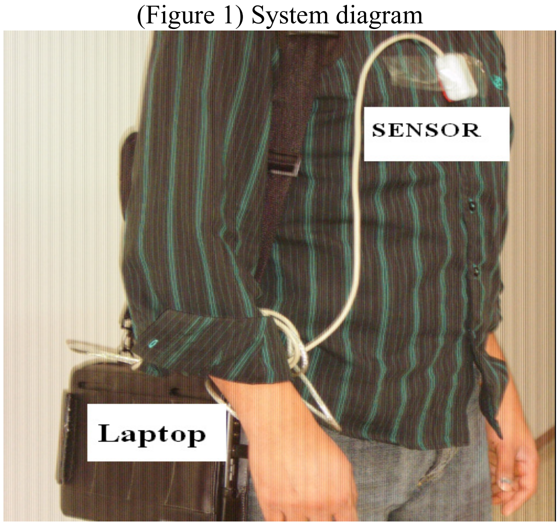
Our real-time system has several sub-components categorized as input, process, and output as shown in Figure 1 and described in Section 3. The rest of the paper is organized as follows: Section 2 describes the experimental setup, Section 3 describes the online system and Section 4 presents the results. Finally, we conclude in Section 5.

2. Experimental Setup and Data Collection

In our setup, we use a portable laptop (Fujitsu LifeBookP1610, 1.20GHz, 1GB RAM) and a tri–axial accelerometer from Spark Fun Electronics (SerAccel V5) [10]. Power of the sensor is gained from a RS232 port connected to laptop: so no external power supply is needed. With the sensor attached to the right chest, we collect continuous data from a person doing activities while carrying the laptop. Our system collects data by interfacing with the COM1 port at 20 points/second rate. The online system uses 200 data points for activity recognition. So, the program recognizes an activity being performed in each 10 seconds. The information such as step counts, energy expenditure etc., however, cannot be calculated in each 10 seconds. Those information are calculated when the exercise is finished by the user, based on the recognized activity.



(Figure 1) System diagram



(Figure 2) Experimental setup

For the training purpose of the recognition algorithm, data is collected from different users at the same 20 points/second rate and labeled for true activities. This way several training datasets are generated so that those data sets can be used for a robust training. Figure 2 shows our experimental setup.

3. Overall System Architecture

Our system is implemented in Matlab [13] for processing and an MS-Access database for storing the calculated information by the system. We configure the MS-Access database as ODBC data source so that we can use built-in MATLAB functions to manipulate the database. The program then takes continuous accelerometer signal as input to recognize the activities performed and extracts the useful information in real-time to export them to database. The information thus generated can be viewed in an information display form in MS-Access. System outputs what activity a user performs every 10 seconds (using 200 data points collected at 20 points/second) and hence the activity recognition system is real-time. The recognition algorithm in the program is trained offline before running the online system.

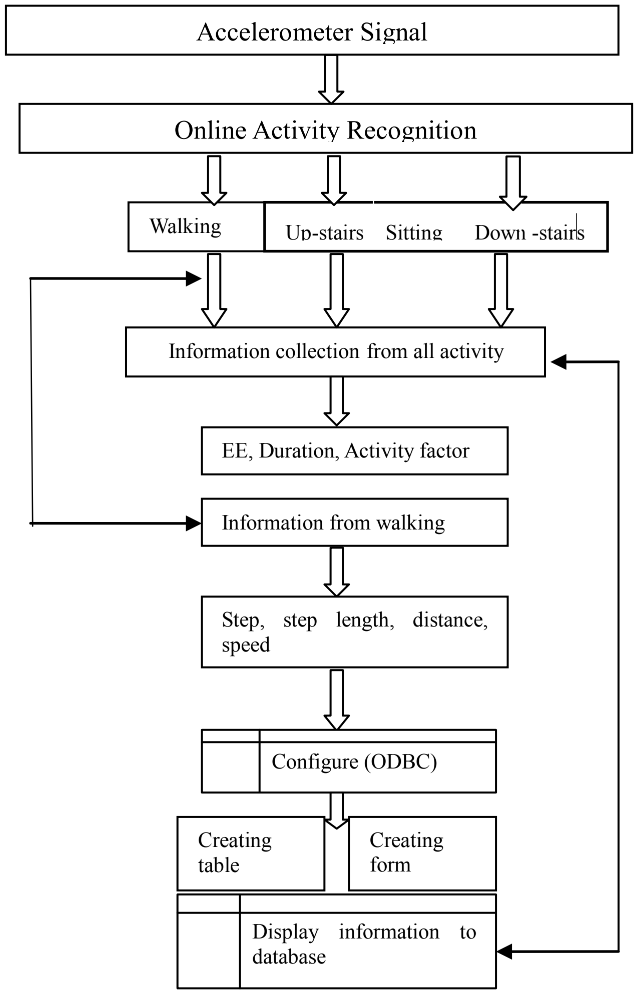
Fig 3 shows the overall architecture of the complete system. Table 1 lists the parameter we get from the system. Basic flow diagram of our online system is shown in Fig 4.

3.1 Online Recognition System

We have used a sliding window to recognize the activities. The window is non-overlapping and consists of 200 points. As the data is collected in 20Hz rate, the window is filled in each 10 seconds. Once the window is filled the recognition algorithm runs and the program outputs what activity the user is performing. The recognition algorithm first calculates AR coefficients, Signal Magnitude Area (SMA) and tilt angle for the signal captured in the window. 5 coefficients are calculated for each of the signal channels. So we get 15 AR coefficients and altogether there are 17 features. The features are arranged as 1-dimensional vector on which Linear Discriminate Analysis (LDA) operation is performed to reduce dimension of the feature set. The resultant vector is then fed to a pre-trained Neural Network for recognition. Details of the training algorithm can be found in [11]. We describe the training algorithm in brief below.

3.1.1 Training of the Recognition Algorithm

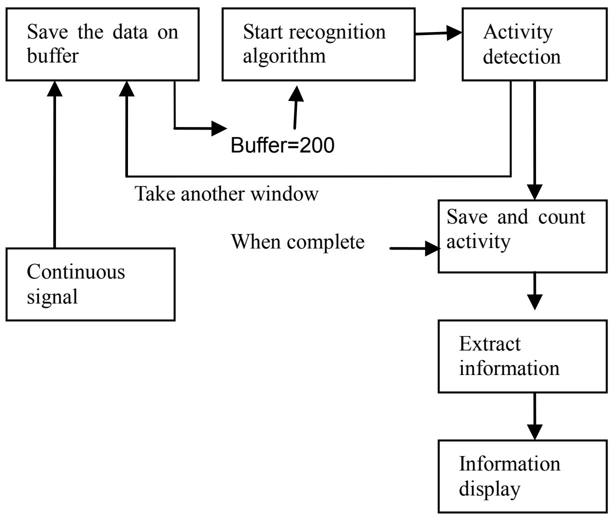
We have collected data from five healthy male subjects aged between 20 to 25. The data is used for training the recognition algorithm used in our online system. Linear Discriminate Analysis (LDA) was used for dimension reduction of the features set. All this features thus calculated are fed to a Neural Network for training. We used a multi-layer back propagation Neural Network. The network was trained using the Levenberg-Marquardt back propagation. We used one hidden layer assigned with eleven neurons and one output layer with four neurons corresponding to the four recognition outputs.



(Figure 3) System Architecture

(Table 1) List of Parameters

Step	BMR (Basal Metabolic Rate)
Step Length	Activity Factor
Speed	Duration
Distance	Energy Expenditure(EE)



(Figure 4) Proposed online system diagram

3.1.2 Information Extraction from the Activities

Our system starts with entering a person's personal information such as gender, age weight, and height as a user input. This information is used to calculate Basal Metabolic Rate (BMR): BMR indicates how much calories we would burn if we were to do nothing but rest for 24 hours, by using well-known the Harris Benedict Formula [9].

During performing various activities we can see our real-time recognition result as what activity is performed for how long and extra activity information such as number of steps, total distance covered, speed, energy expenditure, activity factor, etc. From walking we collect all these information. From upstairs, downstairs and sitting we get only activity factor and energy expenditure. Activity factor is determined from signal by calculating the vector magnitude of three channels X, Y, and Z.

$$AF_a = \sqrt{X^2 + Y^2 + Z^2} \qquad (1)$$

where AF_a is the activity factor. X, Y, and Z are the accelerometer signals of each channel.

Average activity factor is calculated by the following formula:

$$\overline{AF} = \frac{\sum_a D_a \times AF_a}{\sum_a D_a} \qquad (2)$$

where $\overline{AF}$ represents the average activity factor and D_a the duration of the activity, a.

Energy expenditure is calculated from BMR multiplied by average activity factor. So, total energy expenditure (TEE) is:

$$\text{TEE} = \overline{AF} \times BMR \qquad (3)$$

TEE is how much energy we expend during performing different activities. As BMR is fixed for a person, TEE totally depends on the activity that one performs. Total distance of walking activity is computed by:

$$\text{Total Distance} = \text{Number of steps} \times \text{Step length} \qquad (4)$$

The step length for a female subject, S_F and male subject, S_m can be derived as

$$S_F = H_F * 0.413, \qquad (5)$$

$$S_M = H_M * 0.415 \qquad (6)$$

where H_F and H_M represent the height of a female and male subject respectively [12].

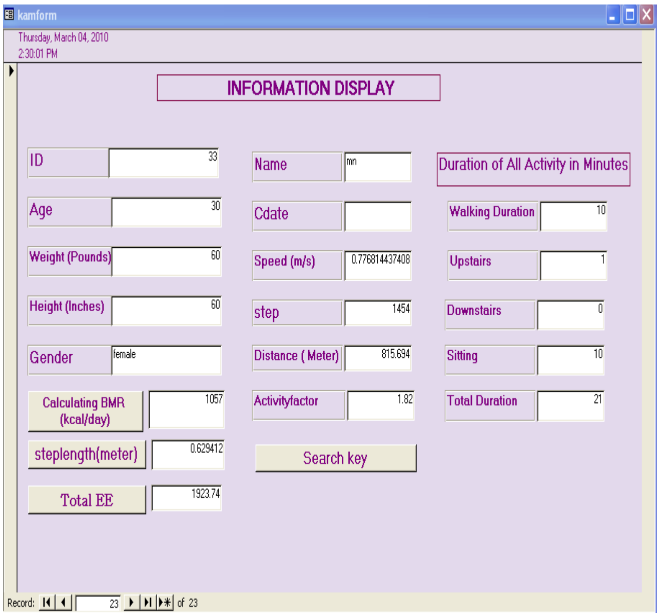
After calculating the parameter values, we validate the results with the ground truth as shown in Table 2.

(Table 2) Parameters

Parameter	Way of Validation
No of Steps	By calculating zero-crossing value of signal and comparing the calculated value with manually counted steps.
Distance(meter)	By calculating according to equation (4) and then comparing with the manually measured distance.
Duration(minutes)	By predefined time assigned for each activity and comparing it with the duration found by the recognition algorithm.
Speed(meter/s)	Calculated by Distance/Duration. Manual value is calculated from the actual distance divided by the time assigned for walking.

3.1.3 Exporting and Storing Information to Database

For storing data and display, we created our own database using MS-Access [14]. We have created table for information storage and forms for information display. Then, we created an Open Database Connectivity (ODBC) connection to access the database from MATLAB. In the front-end MS-Access form, we have to provide some basic information of each subject to calculate BMR. Rest of the information comes from the system during real-time experiment. There are also some searching facilities to find particular subjects information by typing id or name. Here person's ID is set as a primary key to avoid duplicating of data. Snapshot of our display system is given in Figure 5.



(Figure 5) Information display

4. Results

We validated our recognition against the true annotated activity. For example, we planned to walk, going up and downstairs, and sitting for 5 minutes for each activity. If timing information of all the activities is matched with the result of online recognition, we can decide that the system is functioning properly. So, keeping timing information was considered as one of the ground truths for our online recognition system.

We validated our system by testing with different data sets from three different subjects. We recognized four activities, of which three are dynamic and the fourth one is static. The outcome of the validation was quite satisfactory during the experiments with little mismatch with the dynamic activity as given in Table 3 where the results of three cases are represented. In the first case, training data and testing data were collected from different subjects with same gender. In the second case, training and testing subjects were different in gender. In the last case, subjects were same but training and testing dataset were different.

(Table 3) Real-Time Experimental Results

Cases	Activity	Recognition Rate (%)	Mean (%)
1st case	Walking	90	90
	Upstairs	85	
	Downstairs	90	
	Sitting	95	
2nd case	Walking	88	88.25
	Upstairs	90	
	Downstairs	85	
	Sitting	90	
3rd case	Walking	90	92.5
	Upstairs	91	
	Downstairs	90	
	Sitting	99	

While performing the real-time experiment, we also compared our extracted information with the manually calculated data. A comparison for walking activity is shown in Table 4 where the differences between the actual and our system calculated values are nearly same.

(Table 4) Information validation

Activity	Information	Actual Value	Calculated
Walking	Step	340	337
	Distance(meter)	175.5	174
	Duration(minutes)	3.6	3.6
	Speed(meter/s)	0.8125	0.8055
	TEE(kcal)	3667.5	3667.5

5. Conclusion

In this paper, we have presented a real-time daily human activity recognition system using a single accelerometer. We have recognized four primary activities at this moment. We plan to increase more complex activities such as various house hold activities in future.

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