http://dx.doi.org/10.5755/j01.eee.20.5.7113 ELEKTRONIKA IR ELEKTROTECHNIKA, ISSN 1392–1215, VOL. 20, NO. 5, 2014

Method for Recognition of the Physical Activity of Human Being Using a Wearable Accelerometer

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[1]***Abstract*—Companies are interested in retaining workers healthy, productive, and satisfied while cutting health-care and insurance costs. Using a computer at work can cause back, neck and shoulder pain, eyestrain, and overuse injuries of human hands and wrists. It is possible to reduce these risks with better posture and good habits, such as taking rest breaks. During these breaks computer users should be encouraged to stand, stretch, and move around. For people who forget about a break or truly are focused on their direct work need help from special equipment for evaluation of real physical activity of computer user. Method for recording accelerometer data from moving human as he or she performs daily activities and for identification of type, duration and intensity of movements by using wearable wireless sensing system is presented in this paper. The extraction of orientation independent acceleration data has positive effect on recognition accuracy of k-nearest neighbour classification scheme used for classification task. The recognition accuracy of algorithm is 78.9% and these results are better than accuracy obtained from raw accelerometer data. The method presented is simple, exhibited good performance and does not require significant computational recourses.**

***Index Terms*—Accelerometers, motion estimation, biomedical signal processing, classification algorithms.**

I. INTRODUCTION

Using a computer is low effort physical activity when viewed from a total body perspective, but maintaining the same posture for extended periods can lead to problems in localized areas of the human body. Maintaining static postures, such as viewing the monitor, for a prolonged period of time without taking a break can fatigue the muscles of the neck and shoulder that support the head [1]. The jobs that require long periods of static posture may require several, short rest breaks. During these breaks computer users should be encouraged to stand, stretch, and move around. This provides relaxation and allows the muscles enough time to recover. The frequent breaks are more effective to help working body tissues to recover: 3 to 5 minutes every 30 minutes of computer use is recommended [2]. Lithuanian Hygiene Norm HN 32:2004 “Work with Display Screen Equipment. Safety and Health Requirements” requires that people who work at a computer all the day long should take a break every hour for 5 to 10 minutes.

Most people often forget that an hour or more has passed and keep working. For those who are truly focused and need help breaking up their day, there is software available in the market to remind taking a break. But usually computer users are neglecting this warning and continue working. In such a case, special equipment for evaluation of real physical activity of computer user is needed.

By regularly monitoring parameters of physical activity we can determine the motions, evaluate total time of inactivity and control the human physical activity during the break. The classical pedometers used are inaccurate, do not identify a person and its activity type.

The aim of this study was to develop a method for recording accelerometer data of moving human as he performs daily activities such as walking, sitting, jogging, jumping and for identification of type, duration and intensity of movements. The wearable sensing device and special software installed in user’s computer were used for evaluation of the work time duration, physical activity during the break and in general to control labour process of office worker.

II. STRUCTURE OF SENSING SYSTEM

Mobile devices such as smartphones have become a powerful sensing system for capturing the user’s daily activity data in the real world. But one of the most important considerations concerning the practical uses of these applications is the battery life of mobile devices. In this case, additional sensing tasks will consume considerable power therefore different technical solution is needed.

Bluetooth® low energy RF System-on-Chip (SoC) from Texas Instruments [3] with precision sensor interface has become new sensing platform for capturing the human activity information. This chip enables development of wearable sensor as a robust network node transmitting data from tri-axis accelerometer to user computer.

The diagram of the sensing system is shown in Fig. 1. Human body movement accelerations can be measured with low power accelerometers (1). These sensors use I^2C interface and are connected to the cutting-edge Bluetooth low energy System-on-Chip (2). To minimize power consumption sensors are by default disabled and they are in

Manuscript received January 13, 2014; accepted March 15, 2014. This research was supported by Elinta JSC.

sleep mode between measurements. Additionally, short transition times between operating modes of Bluetooth System-on-Chip enable further low energy consumption.

To assess accelerations of the body during movements, the wearable accelerometer is usually placed as close to the centre of gravity as possible. This placement may intuitively seem most appropriate and subsequently have been used [4]. In our case persons carried the wearable sensor in the front pocket of their shirt.

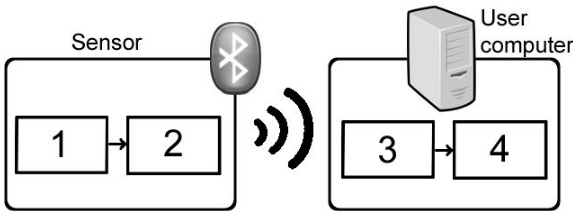

Fig. 1. Sensing system: 1 – 3 axis accelerometer, 2 – Bluetooth Low Energy radio System on Chip, 3 – Bluetooth module, 4 – signal processing software.

Accelerometer data were downloaded to user computer by Bluetooth linkage (3) and analysed using biomedical signal processing software (4). The processed data was used to perform activity recognition and identification of the physical activity a computer user is performing during working day.

III. THE PROPOSED METHOD

The proposed method for human activity recognition based on tri-axis accelerometer comprises the following five steps:

1. Capturing tri-axis accelerometer data of most popular human activities;
2. Extraction of features from accelerometer data;
3. Creating the feature matrix including feature sample vectors of different activities;
4. Collection of data during the whole working day;
5. Recognition of activities in data set representing real life process.

The wearable accelerometer sensor was used to collect data for everyday activities such as low speed walking, high speed walking, sitting, shoulder lifting, squatting and jumping. The dedicated data collection software running on *iPad* was used to collect 5 seconds of accelerometer data (sampling frequency was set to 20 Hz) for each activity type. The software was produced using application builder *techBasic*. The raw accelerometer data often contains high frequency noise, which in many cases distorts the actual signal. So, these data sequences additionally were filtered using a 5-point moving average filter.

For feature extraction only accelerometer data recorded during a stationary state of each activity has been selected. The tri-axis accelerometer data have been used to calculate features for each axis: the average ($\bar{a}_x$, $\bar{a}_y$, $\bar{a}_z$), the standard deviation ($\pm_x, \pm_y, \pm_z$), maximum (max_x, max_y, max_z), minimum (min_x, min_y, min_z), frequency domain entropy (E_x, E_y, E_z), dominant frequency (F_x, F_y, F_z) and average resultant acceleration *ARA* [5]

$$ARA = \frac{1}{N} \cdot \sum_{i=1}^{N} \sqrt{a_{xi}^2 + a_{yi}^2 + a_{zi}^2}, \quad (1)$$

where a_{xi}, a_{yi}, a_{zi} is magnitude of accelerations, measured in *x, y* and *z* direction, *i* is an index of sample, *N* represents the size of recording.

For definition of the harmonic content of the accelerometers signal the power spectral density *P* has been calculated. The frequency domain features of power spectral density are the dominant frequency *F* and frequency domain entropy *E* [4], defined as

$$E = \sum_{i=1}^{N/2} \left[P(i) \cdot \lg(P(i)) \right]. \quad (2)$$

The dominant frequency *F* is the frequency at which power spectral density function has the maximal value.

But accelerometer placement may be in some arbitrary orientation on the human body. In this case different orientations cause acceleration readings varying from person to person for the same activity and using the same equipment. For example, if two people are sitting and wearable sensors are both located in a pocket, the mean values of accelerometer data are: for the first person

$$\left[\bar{a}_x \ \bar{a}_y \ \bar{a}_z \right] = \left[\text{-0.397 -0.921 -0.036} \right], \quad (3)$$

and for the second person

$$\left[\bar{a}_x \ \bar{a}_y \ \bar{a}_z \right] = \left[\text{-0.681} \quad \text{-0.732} \quad 0.001 \right]. \quad (4)$$

It can be seen that ($\bar{a}_x, \bar{a}_y, \bar{a}_z$) readings of one person are significantly different from the other person due to the different orientations of sensor.

One easy solution to avoid orientation problem is using to estimate the gravity component from each segment of (a_x, a_y, a_z) readings because accelerometers are sensitive to both linear acceleration and the local gravitational field. For a chosen 5 seconds sampling interval, the gravity component on each axis was obtained by averaging all the readings in the interval on that axis and normalizing estimated values of each axis separately [6]

$$\bar{G} = \left[\bar{G}_x \ \bar{G}_y \ \bar{G}_z \right], \quad (5)$$

where:

$$\bar{G}_x = \frac{\bar{a}_x}{\sqrt{\left(\bar{a}_x^2 + \bar{a}_y^2 + \bar{a}_z^2\right)}}, \quad (6)$$

$$\bar{G}_y = \frac{\bar{a}_y}{\sqrt{\left(\bar{a}_x^2 + \bar{a}_y^2 + \bar{a}_z^2\right)}}, \quad (7)$$

$$\bar{G}_z = \frac{\bar{a}_z}{\sqrt{\left(\bar{a}_x^2 + \bar{a}_y^2 + \bar{a}_z^2\right)}}. \quad (8)$$

The scalar component of acceleration vector $a_i = (a_{xi}, a_{yi}, a_{zi})$ in the direction of a vector $\bar{G}$, representing amplitude of the vertical components, can be calculated as inner product using following equations [7]

$$v_i = a_{xi} \cdot \bar{G}_x + a_{yi} \cdot \bar{G}_y + a_{zi} \cdot \bar{G}_z. \quad (9)$$

The projection of the acceleration vector in the horizontal plane, which is orthogonal to estimated gravity vector $\bar{G}$, represents movements in horizontal direction. The horizontal magnitude can be calculated as [8]

$$h_i = \sqrt{\left(a_{xi} - v_i \cdot \bar{G}_x\right)^2 + \left(a_{yi} - v_i \cdot \bar{G}_y\right)^2 + \left(a_{zi} - v_i \cdot \bar{G}_z\right)^2}. \quad (10)$$

The waveforms h_i and v_i are independent of orientation of wearable sensor. Using the same acceleration data of two sitting persons, that were previously used for calculation, the mean values of vertical and horizontal components for the first person - $[\bar{v}\ \bar{h}] = [1.002\ 0.0023]$, for the second person - $[\bar{v}\ \bar{h}] = [1.006\ 0.0055]$. So, the acceleration data are orientation independent. In this case, vertical and horizontal components of acceleration vector can be used for calculation of features: the average $(\bar{v}, \bar{h})$, the standard deviation $(\pm_v, \pm_h)$, maximum $(max_v,\ max_h)$, minimum (min_v, min_h), frequency domain entropy (E_v, E_h) and dominant frequency (F_v, F_h).

In this way a two feature vectors have been constructed for each activity: one vector is a features of human activity using raw accelerometer data, second vector represent human activity features calculated from orientation independent data. If the features of all human activities are extracted, the feature matrix size is *n* by *m*. Value *n* is the number of features (in first case *n = 19*, in second case *n = 12*). Value *m* is the number of different activities, that human are performing during working day. Each row of feature matrix contains features from one activity. Columns represent feature value changes for different activities.

For teaching the system each feature values have been calculated as average from five estimations of the same activity performed using different clothes, shoes and at different time of the day. Feature matrix was stored in user computer memory.

The *k*-nearest neighbour classification scheme was used for recognition of activities in everyday activity representing accelerometer data set [9]. The *k*-nearest-neighbour classifier is commonly based on the Euclidean distance between a test sample and the specified training samples, but this metric can become very noisy for high dimensional problems where only a few of the features carry the classification data. To solve this problem the correlation distance has been used. This function looks at similarities in the shape of two traces rather than the exact values of the data, so it is acceptable for the comparison of activity feature data. The definition of the correlation distance function [10] is given by

$$d_{st} = 1 - \left| \frac{(n-1)\sum_{i=1}^{n}(s_i - \bar{s}_n)\cdot(t_i - \bar{t}_n)}{\sum_{i=1}^{n}(s_i - \bar{s}_n)^2 \cdot (t_i - \bar{t}_n)^2} \right|, \quad (11)$$

where *n* – the size of feature vector, s_i – the values of sample vector, representing features of single activity, t_i – the values of vector, representing features extracted from one frame of real activity representing data, $\bar{s}_n$ – average of all sample vector values, $\bar{t}_n$ – average of all real activity representing feature vector values.

During classification stage the values of vector, representing features extracted from one frame of human real activity accelerometer data, are compared with the values in the feature matrix, created during the third step. Because the number of nearest neighbours has been selected as *k = 1*, then the frame is simply assigned to the class of single nearest neighbour, representing the corresponding activity. This frame is labelled as the activity for which the vote is the highest. The classification was repeated using next frames of real accelerometer data and all frames were labelled. Finally, number of frames for each activity was calculated and total time of higher physical activity evaluated during the break. If the physical activity is not intense or long enough the software locks the user's computer until the necessary amount of activity is reached.

IV. EXPERIMENTAL INVESTIGATION OF METHOD

Presented method has been tested with 5 subjects: 2 females and 3 males. All persons carried the wearable sensor in the front pocket of their shirt during training phase and experimental test. Using training data the feature matrix for each of subjects has been formed. Later each subject performed the same activities in random order.

The wearable sensor has been produced on the basis of Bluetooth® low energy RF System-on-Chip *CC2541* and low power, low noise, wakeup interrupt accelerometer *KXTJ9* from Kionix. Thri-axial accelerometer data has been collected on i*Pad* using data collection software produced on *techBasic.* Additionally, all subject motions have been captured by using *Merlin F-146C* camera from Allied Vision Technologies GmbH. Accelerometer data collection and video capturing was started synchronously by using camera external trigger signal from small tactile sensor installed in touch screen pen for *iPad*. Camera is working in Trigger Mode 15, combining one external trigger event with continuous internal trigger. In this case, by touching the *Start* button on touch screen of the tablet the camera starts capturing predefined amount of images. A collected accelerometer data have been separated into a number of fixed size partially overlapping frames. The size of each frame was 100 samples (5s time interval) [11]. The following features were extracted from each frame: the average, the standard deviation, maximum, minimum, frequency domain entropy and dominant frequency. The same test scenario was repeated 5 times with different clothes of each subject. At the end of classification process the accelerometer signal of z-axis and labels of activities were displayed (Fig. 2).

Activity recognition accuracy was evaluated by viewing recoded video and creating vector with the true class labels for each observation frame (5 s). This vector was compared with classification results, obtained using presented method. The correct solutions rate was selected as recognition accuracy parameter. It can be calculated as ratio between correctly classified frames to all classified frames

Table I shows the confusion matrix when the vertical and horizontal components of accelerometer signals were classified using k-nearest neighbour classification scheme. Overall, the recognition accuracy was 78.9 %. Most of the faults of the classification resulted from failure to distinguish between the shoulder lifting signals and the squatting signals. The low recognition accuracy of human activity type was not unexpected. The duration of individual activity during the brake is short (10-20 s) comparing to frame size used to separate all accelerometer data. In this case, individual frame is the overlapping of two activities (complex activity) and features of separated data set are different from features representing poor activity data. But these results are significantly better than recognition accuracy obtained from raw accelerometer data. The recognition accuracy of human activities during a break was only 62.2 %. The presented method by using sensor orientation independent data allows to increase human activity recognition accuracy. The raw accelerometer data can be used for long duration activities or for evaluating human activity during the all working day [12]. If individual activity is simple and longer than a few minutes, it can be recognised correctly by using big frame size (10s and more [13]).

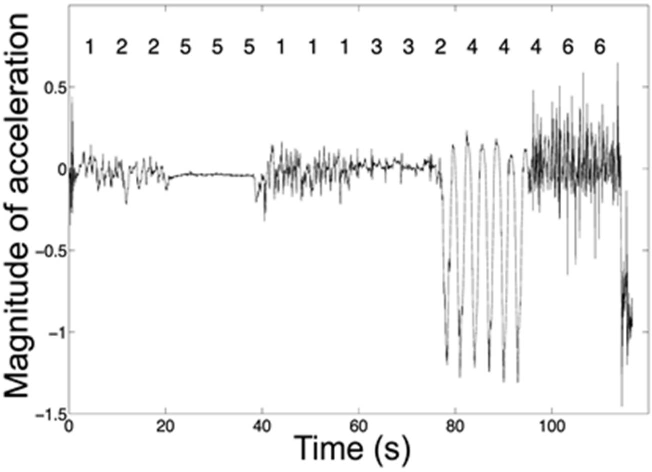

Fig. 2. Acceleration measured during the experimental protocol. Label highlight the signal measured during the tasks included in the test: (1)-high speed walking; (2)-low speed walking; (3)-shoulder lifting; (4)-squatting; (5)-sitting; (6)-jumping.

TABLE I. RECOGNITION ACCURACY.

		Predicted class					
		Low speed wal-king,%	**High speed wal-king,%**	**Sitting, %**	**Shoulder lifting, %**	**Squatting,%**	**Jumping, %**
Actual class	**Low speed walking**	88.9	0	0	0	11.1	0
	High speed walking	11.1	83.4	0	5.5	0	0
	Sitting	8.33	0	83.3	8.33	0	0
	Shoulder lifting	0	5.4	5.56	66.7	22.2	0
	Squat-ting	0	11.1	0	5.56	77.8	11.1
	Jumping	0	5.56	0	0	5.56	88.9

On the other hand, the goal of the system is to evaluate human physical activity during the break and to check if human is active or not. In this case, it is necessary to recognise is person sitting or he is more active during the break. The activity recognition task is not so complicated for this purpose.

The presented method for device orientation correction has large positive effect on the activity recognition accuracy of k-nearest neighbour classification scheme. This result differs from results obtained by using other classification algorithms [14]. So, selected feature vector and classification scheme require orientation correction.

Additionally, the influence of individual features to activity recognition accuracy was evaluated. It was found, that minimum of acceleration data are not important for classification and can be removed from feature vector. Furthermore, the vertical acceleration component is sufficient information for most activity recognition.

V. CONCLUSIONS

The proposed activity recognition method and equipment can be used for human activity evaluation. The wearable wireless acceleration sensing system using Bluetooth low energy System-on-Chip has been designed and implemented to evaluate human body motion. The presented algorithm for extraction of orientation independent acceleration data has positive effect on the activity recognition accuracy of k-nearest neighbour classification scheme. The recognition accuracy is 78.9 % and it is significantly better than recognition accuracy obtained from raw accelerometer data. For more accurate recognition neural network or support vector machine (SVM) classification schemes can be used.

The presented method is simple, exhibited good performance and does not require significant computational recourses, allows data collection for long time periods using small battery as a power source. As a future work, more activities will be added to the classification states and more experimental tests will be carried out with more persons.

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