Mobile sensing platform for personal health management

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***Abstract*—This paper presents a smartphone based portable activity recognition system to record and recognize daily activity patterns of users. This system can assist patients and any individual to better understand their unhealthy behavior, however, making them to change that behavior by improving their daily level of physical activity.**

Keywords—activity recognition; classification models; accelerometer; smartphone

I. Introduction

Context awareness is a vital part of pervasive computing, and human activity recognition (HAR) has emerged as one of the important tools for identification of user's context for automatic service delivery in ubiquitous application. Activity recognition is simply continuous monitoring of physical activity in a free living environment for prolonged periods. HAR provides new opportunities for context aware applications in various areas including healthcare [1, 2], assisted living, sports coaching, security, virtual reality and wearable computing. For example, in area of ubiquitous healthcare applications, the ability to recognize everyday activities could enable such systems to monitor and learn any changes in daily behavior of an elderly which might be the indication of developing mental or physical medical conditions. Thus, such systems can improve the quality of life, health, security, freedom and safety of the elderly population at home [3]. In addition to, patients with heart disease, diabetes, or obesity are often required to follow a well-defined exercise routine as part of their treatment. Therefore, recognizing activities such as resting, jogging, walking or running becomes quite useful to provide feedback to the caregiver about the patient's behavior. Not only applicable to patients, but visualizing everyday physical activity can help individuals to better understand their own unhealthy behavior, however, making them more likely to change that behavior and improve their daily level of physical activity.

This paper reports an investigation on how we can empower users with unobtrusive context aware devices for daily activity recognition using smartphone low level sensor data. The smartphone application developed through this study automatically records the user's physical activity, allowing them to observe their own daily activity patterns. The logged data can allow clinicians to provide detailed exercise prescriptions and suggest improvements to their patients.

II. Methodology

A. Data Collection

Through this study, we have developed a personal health management system which visualizes daily physical activity using smartphone accelerometer signals and location information. In order to collect data for our supervised learning task, activity data was collected from 50 subjects (30 males and 20 females) between the age 21 and 35 years old, with an average height of 172cm and average weight of 67kg. Subjects were members of staffs and students at Mokpo National University, Department of Engineering. These subjects carried the Android phone in their front pants leg pocket and were asked to walk, jog, ascend stairs, descend stairs, stand and lay down for specific periods of time. The data collection process was controlled by a smartphone application. This application, through a simple graphical user interface, permitted to record the user's ID, start and stops the data collection, and label the activity being performed. Before initiating data collection, the subject would select the ground truth for the activity on a custom designed phone app. The accelerations were labeled according to the activity they were performing. The acceleration signals were sampled at 20 Hz and stored on a Secure Digital card in the Smartphone. For this study, we have used this raw data for feature extraction and building classification model using WEKA [4].

B. Data Processing and Classification

For the machine learning approach a number of time domain features were extracted from the collected accelerometer data. These features were mean, standard deviation, mean absolute deviation, time between peaks and resultant magnitude. These features were then used as input for WEKA data mining software to build the classifiers. Eight different classification algorithms were applied to the data. These include: Bayesian Network (BN), Multilayer Perceptron (MLP), Naïve Bayes (NB), the C4.5 Decision Tree (J48), Random Tree (RT), Radial Basis Function Network (RBFNet), Sequential Minimal Optimization (SMO) and Logistic Regression.

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III. Results and Discussion

In total eight classifiers were evaluated with five different random seeds $s_i = \{1, 128, 255, 1023, 4095\}$. Table I shows the results of the 5x2-fold cross validation for the accelerometer dataset. Note that the highest overall accuracy was achieved by the *J48* classifier (i.e., 95.156%). In order to find the best classifier for the dataset, a paired two-tailed *t*-test was performed between the J48 and all other classifiers with a significance level $\alpha = 0.05$. The null hypothesis is that each pair of classifiers achieved the same mean accuracy. As a result of the tests, the *p*-values are included in the last column of Table I. Since all the *p*-values are below the significance level, there is strong statistical evidence that *J48* is more accurate than all other classifiers in the tested dataset. The confusion matrix for the best classifier, *J48*, is shown in Table II after five iterations using five different random seeds.

TABLE I. Percentage Classification Accuracy Given by the 5x2-Fold Cross Validation

	s_1	s_2	s_3	s_4	s_5	Avg.	*p*-value
BN	76.82	77.81	77.19	77.38	77.29	77.30	<0.001
MLP	93.90	94.44	93.86	93.86	94.14	94.04	0.001
NB	58.06	57.60	57.42	57.70	56.48	57.45	<0.001
J48	**94.97**	**95.15**	**95.03**	**95.40**	**95.20**	**95.16**	-
RT	93.67	94.40	94.48	94.67	94.51	94.35	0.004
RBFNet	72.02	71.79	71.03	73.03	72.77	72.13	<0.001
SMO	89.48	89.78	90.11	90.27	89.71	89.87	<0.001
Logistic	91.90	92.60	92.45	92.71	91.77	92.29	<0.001

TABLE II. Confusion Matrix for the Best Classifier *J48*.

	Predicted Class						
	Walk	Jog	Stairs	Sit	Stand	Lay Down	% Correct
Walk	2204	2	20	14	6	4	97.96
Jog	6	161	9	3	2	3	87.50
Stairs	31	5	212	1	2	0	84.46
Sit	18	4	7	1425	22	11	95.83
Stand	5	1	1	12	842	4	97.34
LayDown	5	2	0	19	6	587	94.83

In order to generate predictions on the user's activity, the alphanumeric representation of the Decision Tree model, as given by the WEKA output, was implemented in Java. Fig. 1 displays some of the screens of the activity recognition app.

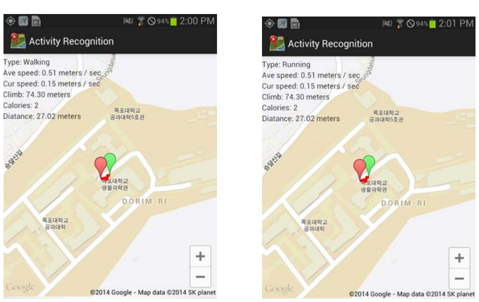

Fig. 1. Mobile Application User Interface

Since this research focuses on the investigation of daily user physical activity, recording and recognizing these daily activity was necessary. Therefore, each activity was stored in the database on the smartphone. The user's statistics (e.g., activity type, average speed, calories burnt and distance travelled) and user location in real-time was also displayed on the smartphone app. This sequence of individual's activities can be visualized as personal chart journal as illustrated in Fig. 2 and Fig. 3.

Fig. 2. Activity level of an individual per day

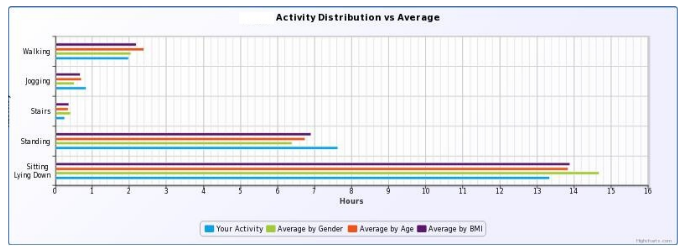

Fig. 3. Average Activity level of multiple users per day

IV. Conclusion

This work implemented a portable activity recognition system to analyze the pattern of the user's daily physical activity through a smartphone application. The experiments indicated highly accurate activity pattern recognition through cross validation and paired *t*-test. Future work is to include other sensors available on the smartphone to perform the desired activity recognition.

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