User Activity Recognition Based on Smart Chair with Pressure Sensors

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***Abstract*—This paper presents a smart chair that is able to recognize three daily activities whiles seated. The smart chair is built from six mounted pressure sensors on a chair and a raspberry pi to collect raw data. We used Random Forest classifier to identify whether the user is eating, napping, or working on PC. The system is tested and the accuracy is above 97%.**

I. INTRODUCTION

The most predominant daily activities performed by most people is sitting. Most of the daily activities performed whiles seated includes working in the office, having a meal, taking a nap, watching a movie, playing games, etc. Moreover, the chair is ubiquitous and widely used in offices, schools, hospitals and home. A chair usage study is performed with 50 participants which concludes that 50% of user spent more than 9 hours sitting daily and 20% of users spent more than 14 hours sitting daily [1]. Previous research used four pressure sensors with random forest classifier to classify 18 different activities performed whiles seated. Their model accuracy is 86% [2]. Our study used six pressure sensor to identify three activities among all activities performed by eight different users whiles seat. These activities includes eating, working on PC and napping. Our model accuracy is above 97%.

II. SYSTEM DESIGN

A. Hardware Design

Smart chair is composed of a regular office chair with two square Force Sensitive Resistors (FSRs) on the backrest and four on the seat as shown in Fig.1.

B. Data collection

We collect the data for three activities from eight users, three men and five women. All of the three activities were performed separately. The users performed all these activities as naturally as they can. The time period for each activity was 10 minute. During emulating the activities, they used an office desk to place the plates and computer. We set a webcam to record video of the activities simultaneously. The video was recorded with a timestamp in order to verify the collected data in case of any abnormality observed. For labeling activities, we refer to video and labeled manually based on the timestamp. The raw data size collected from all users after performing all the activities mentioned above was 507,370 data points. The sampling rate of raw data is 30 samples per second.

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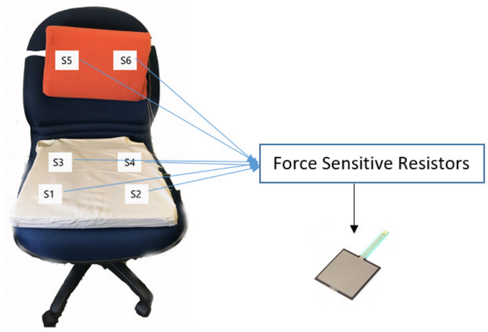

Fig.1. Force Sensitive Resistor placed on the seat and backrest of chair. All sensors mounted inside the cushion.

C. Feature selection

Feature selection is often an essential data processing step prior to applying a learning algorithm [3]. To improve our model accuracy, we selected 24 features from the raw data for all sensors. For each raw signal from the sensor, we selected the mean and variance from the signal in time domain as well as in frequency domain. These features selected from a sliding window of size 30 with 50% overlapping which correspond to one second of sensor time [4]. After selecting the two features in time domain, we used Fast-Fourier Transformation (FFT) to transform the data to frequency domain and select the same features [2]. Our training data consists of 24 features, which is the column-wise combination of all the selected features in each sensors.

III. IMPLEMENTATION RESULTS

A. Experiment Results

In order to verify the performance of our experiment, we implement two experiment cases. The first is user-dependent and the second is user-independent. User dependent is that the data of test users included in training data set, and user-independent is that no data included in the test data if test users is included in training data set [5].

1) User-dependent

The feature data from feature selection consists of 33,823 feature points. The training and testing data consists of 25,365 and 8,456 feature points, respectively. The feature sizes of each activities for user-dependent are outlined in Table I.

TABLE I
FEATURE SIZES OF USER-DEPENDENT

Activity	Training	Testing
Eating	8,759	2,927
Working on PC	8,421	2,794
Napping	8,185	2,735
Total data	25,365	8,456

Random Forest classifier was trained on the training data. The hyper-parameters of the model is depicted in Table II.

TABLE II
HYPER-PARAMETERS OF RANDOM FOREST

Parameters	Value
n_estimators	20
max_features	30
oob_score	True
random_state	20
num_trees	500

Our model predicted each activity based on the features. The testing data feature is 8,456 feature points. The testing accuracy was 97%. The confusion matrix obtained with Random Forest classifier is shown in Table III. This clearly manifested that, all three activities have accuracy above 96%.

TABLE III
CONFUSION MATRIX OF USER-DEPENDENT

	Eating	Napping	Working on PC
Eating	**0.9836**	0.0163	0.0003
Working on PC	0.0345	**0.9642**	0.0026
Napping	0.0022	0.0066	**0.9912**

2) User-independent

For user-independent we split the features data in to two parts. Four users for training and four users for testing. The data for training is not included in testing. The feature sizes of each activities for user-independent are outlined in Table IV.

TABLE IV
FEATURE SIZES OF USER-INDEPENDENT

Activity	Training	Testing
Eating	4,392	1,436
Working on PC	4,212	1,436
Napping	4,078	1,356
Total data	12,682	4,228

The testing accuracy for user-independent is 96%. Table V is the confusion matrix of user-independent. From the table below, activity of eating has the highest accurate of classification which has the smallest number of wrong classification.

Based on two kind of experiments that are user-dependent and user-independent, the accuracy of user-dependent is higher than user-independent.

TABLE V
CONFUSION MATRIX OF USER-INDEPENDENT

	Eating	Napping	Working on PC
Eating	**0.9791**	0.0213	0.0000
Working on PC	0.0586	**0.9387**	0.0067
Napping	0.0045	0.0120	**0.9838**

IV. CONCLUSIONS

In this paper, we are able to classify user activities for sedentary. With embedded six sensors in the chair and mounted four sensors in the seat and two sensors in the backrest are an effective way to perform higher accuracy with extract more features. The Random Forest classifier has been used to evaluate the informative tested of these features to classify the activities. Very high classification performance has been reached, obtained up to 97% for user-dependent and 96% user-independent. Based on the results obtained using three activities, future works plan to observe another activity to get more information from the users.

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