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Care-Chair: Opportunistic health assessment with smart sensing on chair backrest

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CARE-CHAIR: OPPORTUNISTIC HEALTH ASSESSMENT WITH SMART SENSING ON CHAIR BACKREST

by

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ABSTRACT

A vast majority of the population spend most of their time in a sedentary position, which potentially makes a chair a huge source of information about a person's daily activity. This information, which often gets ignored, can reveal important health data but the overhead and the time consumption needed to track the daily activity of a person is a major hurdle. Considering this, a simple and cost-efficient sensory system, named Care-Chair, with four square force sensitive resistors on the backrest of a chair has been designed to collect the activity details and breathing rate of the users. The Care-Chair system is considered as an opportunistic environmental sensor that can track each and every activity of its occupant without any human intervention. It is specifically designed and tested for elderly people and people with sedentary job. The system was tested using 5 users data for the sedentary activity classification and it successfully classified 18 activities in laboratory environment with 86% accuracy. In an another experiment of breathing rate detection with 19 users data, the Care-Chair produced precise results with slight variance with ground truth breathing rate. The Care-Chair yields contextually good results when tested in uncontrolled environment with single user data collected during 8 hours of study.

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1. INTRODUCTION

Good health is the greatest asset to any individual. The definition for good health varies from person to person based on their gender, age, physical ability, environmental conditions, occupation and lifestyle. The parameters for the physical or mental fitness of a person involved in sports, the Army or other such activities are viewed differently than for a person primarily involved in less physically active occupations like computer professionals, teachers or office employees. Similarly, the health conditions of elderly people or the physically challenged are evaluated and monitored differently than comparatively younger, energetic and fit people. In general, there are four vital health signs used to evaluate the medical conditions of a person. These are body temperature, pulse rate, respiration rate and blood pressure. Doctors advice keeping track of these vital health signs regularly and periodically to maintain a healthy body. Very few seriously follow this instruction. More often, the majority of population uses their busy schedule as an excuse. The other major factors for negligence towards basic health care are ignorance, lack of knowledge of consequences, laziness, lack of proper resources and even deliberate avoidance. A very small part of the population, those who are either extremely health conscious or those already suffering from health related problems, visit health centers for regular checkups. Considering all of the major hurdles causing an individual to be reluctant to basic health care monitoring, many companies have come up with wearable health care devices that can record and keep track of vital health signs. This was a big revolution in health care by providing users with the ability to monitor their health independently and continuously despite their busy schedule. The wearable devices like Fitbit, smart watches and ECG (Electrocardiogram) are a few of them.

But as we know that nothing comes for free, these wearable devices have certain limitations. All of these devices operate on battery. The batteries are rechargeable but they consume considerably more energy than usual due to their high processing power. The limited energy storage capacity of batteries limits the use of these wearable devices and ends up annoying users to recharge them more frequently. Moreover, the size and overhead to wear it all the time demotivates fashion-loving people to use it. Since these devices are sophisticated as well as expensive, they are not widely accepted by the economically under-privileged, elderly and less technology savvy population. Furthermore, sometimes the user forgets to remove the device during activities like bathing, washing dishes, and other activities involving water. This may cause damage to the circuit of the device and collapse its functionality. Even if the devices are removed as a precaution to avoid the damage, the users generally forget to wear it again later on. Interestingly, in some cases people consider using these devices as a privacy breach and security threat. For example, ECG (Electrocardiogram) on a person's body reveals that the person has some heart related issues. Knowing this an attacker with malicious intent could easily target that person. Any activity or incident that can bring sudden excitement can drastically increase the heart beat, which is life-threatening for heart patients.

The limitations and drawbacks of wearable healthcare devices promote the requirement of environmental sensors or devices that can opportunistically collect the health-related information without any human intervention and effort. Environmental devices can also be called "implicit sensors". The concept of implicit sensors or devices utilizes a few selected materials or objects present in a person's surrounding that are in frequent interaction with a him or her during daily activities. Such materials might be a bed, personal computers, chair, clothes, etc. The primitive selection of such objects depends on certain criteria like the amount of time an individual spends with it, the way that object is being used, acceptance rate of the object from the majority of the population, and the mode of utilization of the object, i.e. personalized or shared among multiple users. The interaction time with the objects chosen for implicit sensing is important, as the more time a person spends with the object, the better the quality and quantity of health information will be. Furthermore, it is extremely important to observe the way an object interacts with a person in order to determine its usability.

1.1. MOTIVATION

Most of the people spend a major portion of their daily working time in sedentary position. Moreover, the chair is ubiquitous and widely used in offices, schools, hospitals and home. In a chair usage study performed with 50 users in [10], 55% of users spent more than 9 hours a day in sitting position and 20% of users spent more than 14 hours. Also, 91% of users claimed to have a primary chair, and 61% of users were the only occupant of their primary chair. Most importantly, the fact that 67% of users frequently use the backrest of their chair motivated the use of a chair as the system design for an environmental sensor.

2. RELATED WORK

There are many of existing works that explore coverting various objects that surround humans into environmental sensors that can opportunistically collect data without any human intervention. These objects can be items like clothes, furniture, parts of automobiles (like a steering wheel or seat), computer keyboards, etc. Because the discussion is related to using the chair as an environmental sesnors, this section contains a review of the existing literature on this subject.

2.1. STATIC POSTURE DETECTION WITH CHAIR

Tan et al. [22] used commercially-available pressure distribution sensors developed by Tekscan [1], which were mounted on the seat and backrest of a regular office chair to sense and understand the occupant's activities and needs. A principal components analysis (PCA) based algorithm has been developed for real time static posture classification. This algorithm attained a classification accuracy of 96% when training and testing datasets were from familiar users, whereas a 79% classification accuracy was attained when different user datasets were used for the training and testing. The 14 different sitting postures that were classified are: (1) seated upright, (2) leaning forward, (3) leaning left, (4) leaning right, (5) right leg crossed (with knees touching), (6) right leg crossed (with right foot on left knee), (7) left leg crossed (with knees touching), (8) left leg crossed (with left foot on right knee), (9) left foot on seatpan under right thigh, (10) right foot on seatpan under left thigh, (11) leaning left with right leg crossed, (12) leaning right with left leg crossed, (13) leaning back, and (14) slouching.

Like the commonly used Tekscan pressure mats, Meyer et al. [16] designed their own textile pressure sensor array that can measure the pressure distribution while sitting.The textile sensor was consisted of 240 sensor elements. Due to the large number of sensing points it was difficult to fit the textile over the seat area of the chair. Hence, the textile was folded in layers, and each layer was separated with non-conductive textile to insulate the two conductive layers. Wires from each layer were connected to the electrodes. Commercially available Tekscan pressure mats were also placed on the seat, in addition to the textile sensors,to validate the pressure distribution detection by the textile sensors. The Naive Bayes classifier was applied to identify 16 different sitting postures on the chair: (1) seated upright, (2) leaning right, (3) left, (4) forward, (5) back, (6) left leg crossed over the right, (7) right over left, (8) once seated upright, and (9) once leaning back, (10)-(13) once while the knees are touching and once with the ankle rested on the leg, (14) slouching, (15) sitting on the leading edge and (16) slouched down. Among the other works, Mutlu et al. [18] used 19 square pressure sensors at different calculated locations on the seat and backrest of the chair. They used values for a total of 30 features from the training dataset and then trained the classifier based in logistic regression to classify 10 various sitting positions: left leg crossed, right leg crossed with leaning left, leaning back, leaning forward, leaning left, leaning right, left leg crossed with leaning right, seated upright, right leg crossed, slouching.

Fu et al. [9] developed an intelligent chair capable of predicting the subsequent sitting activity of the occupant based on his or her classified sitting posture.A total of 8 force sensing resistors (FSR) were placed on the backrest and seat of the chair and a Raspberry Pi board was used as the middleware for the IntelliChair system. The major tasks performed by the Raspberry Pi board included collecting raw data from the pressure sensors, processing data, classifying postures, and recognizing and predicting activity. Based on the experiments conducted with different classification algorithms, they found the decision tree as the best classifier for ItelliChair. The static activities that were detected include back postures (body leaning right, leaning back, body leaning left and no contact) and leg postures (sitting upright, crossing right leg on left leg, crossing left leg on right leg, sitting forward and no contact).

Similarly, ExerSeat [6] tracks the occupants sitting posture and suggests appropriate exercises to prevent health problems from prolonged sitting at the workplace. Using 8 capacitive proximity sensors mounted on the seat and backrest of the chair, ExcerSeat supports posture recognition for five different exercises: (1) back bend (moving the torso region left and right), (2) back up (touching the feet with a fixed sitting position by lowering the upper body to the legs), (3) bicycles (sequentially raising the left and right leg from the chair), (4) squat (standing up from the chair and sitting back down with arms stretched to the front), (5) sit up (sitting upright on the front of the seat, lowering straight back to the backrest, and coming back up).The pressure array mat from Tekscan was also used in [23] to find static postures of users using an unsupervised machine learning method.The unsupervised classification mostly generated 16 distinguishable static sitting postures for the users under the experimental setup. A total of 16 postures were recorded during the posture experiment: (1) sitting upright, default posture, (2) leaning left, (3) leaning right, (4) leaning back, (5) leaning front, (6) left legover right, knees touching, upright, (7) right leg over left, knees touching, upright, (8) left leg over right, knees touching, leaning back, (9) right leg over left , knees touching, leaning back, (10) sitting on leading edge, (11) lying, (12) slouching, (13) left leg over right, foot on knee, upright, (14) right leg over left, foot on knee, upright, (15) left leg over right, foot on knee, leaning back, (16) right leg over left, foot on knee, leaning back.

2.2. USER ACTIVITY DETECTION WITH CHAIR

The work in [7] by Cheng et al.placed simple pressure sensors under the leg of the chair to extract 7 different sitting postures along with the occupant's hand and head movement during activities like typing and nodding. In the experiments with

5 user datasets, the authors achieved a classification accuracy of 82.6% for 7 sitting postures: (1) sitting straight, leaning (2) left / (3) right / (4) forward / (5) backward, (6) raising one hand and (7) crossing one leg over the other knee). In addition, they conducted experiments with 5 users to show that the subtle actions related to arm, hand and head motions produce certain signatures which are detectable using the pressure sensors. Using the hand and head movements, they recognized the following 5 activities with 88% accuracy: (1) typing on a keyboard, (2) clicking a mouse, (3) nodding, (4) clapping hands, and (5) sitting still.

Another work on the GRiT chair alarm [14] used pressure sensors to detect the occupant's (patient in this case) gesture, and then probabilistically determined the likelihood of the body collapsing and generated an alarm to notify caretakers. But the work also uses 7 capacitance sensors placed at the various heights along the chair's backrest to measure the distance between the backrest and the patient's back. In addition to that, 12 pressure sensors were located on the seat and the armrest of the chair to determine the occupants contact position and weight distribution. Interestingly, the chair generated an alarm when it detected the occupant falling to convey the information to the caretaker via WiFi networks. In another category of work, the authors in [20] proposed an acoustic-based head orientation estimation method using a microphone array mounted on a chair. Another work in [21] develop a noise robust speech recognition system for a voice-driven wheelchair with a microphone array unit integrated on the chair. The SenseChair work theat was conducted by Forlizzi et. al. [8] explored the various possible ways an elderly person can interact with his or her personalized chair and tried to provide an assisted living environment so that users can stay independently in their homes. The seat of the SenseChair was covered with a smart fabric cover with pressure sensors sewn on it. There were 6 pressure points with a configuration of 4 sensors at 4 corners of the seat and 2 sensors on the middle. In addition, SenseChair used 8 halogen lamps arranged in a circular fashion beneath the seat of the chair and 18 vibration motors distributed on seat cushion and back cushion of the chair. All these configuration in the SenseChair were used to create different kinds of alerts and signals to assist the user based on his or her requirement.

2.3. STRESS AND ATTENTION DETECTION WITH CHAIR

The pressure distribution sensors by Tekscan were also used by Arnrich et al. [3] to determine the stress level of the chair's occupant based on movement signatures. In the study the users were first asked to perform certain activities under given conditions, making the task stressful. Then, they were asked to perform the same tasks freely without any such conditions. The proposed method was used to extract features derived from the spectra of norm of the center of pressure (CoP). The features were extracted for each user during both forms of study: the stressful condition and the control condition. The stressful condition consisted of performing mental arithmetic problems under the pressure of a time constraint and a social-evaluative threat. The control condition consisted of performing mental arithmetic with the absence of both time pressure and social evaluation, which is similar to working normally on a computer. The proposed method utilized self-organizing map (SOM) based classifiers and a XY-fused Kohonen network to handle different patterns of the subject's stress responses and determine the stress levels of the occupants.

The pressure sensor array by Tekscan was also used in the work [13] for posture detection of a sitting user. The goal was to classify interest and disinterest in children who were solving an educational puzzle on the computer. However the proposed system uses multiple sensor modalities with facial image recognition, postures, and task information. The pressure sensor array is used only for detecting some postures (such as sitting upright and leaning back) and assessing activity level (low, medium and high). Another work by Mota et al. [17] studied the sitting postures and their patterns again to detect the interest level of children in a learning environment. The sequence or patterns of sitting postures was determined using a set of independent hidden Markov models, which can categorize the child's interest into three levels of high, medium and low.

2.4. BODY VITALS DETECTION WITH CHAIR

Bolstering the works on measuring the vital health signs like heart rate through a ballistocardiography (BCG) technique, Junnila et al. [12], [11] used an EMFi-film sensor installed on the seat of the chair. They have used a blind segmentation method to filter out the BCG cycle from other dominant interferences like body movement, respiration and electrical noise. The work in [4] uses the chair back with a capacitance-coupled sensing method to measure biological signals like electrocardiogram (ECG), photoplethysmogram (PPG) and ballistocardiogram (BCG) and promotes the chair as a non-intrusive sensor [15] for measuring vital health signs. Postolache et al. [19] used the backrest and seat of a chair to monitor heart rate and respiration rate. They mounted the EMFi (electromechanical film) sensors on the chair and then performed Wavelet based data processing on the obtained ballistocardiographic (BCG) signals from human subjects. Eight capacitive proximity sensors were installed at different locations on the capacitive chair [5] to detect respiratory rate, body posture and activities. Ford's research lab [2] is developing a sensor that can be embedded on the backrest of a car seat in order to monitor the driver's heart rate without any contact with the skin. Griffiths et al. [10] placed the pressure sensors on the backrest of the chair and an EKG sensing element on the armrest. Using an autocorrelation method on the obtained pressure data, they calculated the breathing rate of the chair occupant. Similarly, using another R-peak detection method they calculated the heart rate of the occupant from the EKG signal.

3. CARE-CHAIR SETUP DESCRIPTION

Care-Chair is basically a simple regular chair (Figure 3.1) with backrest embedded with just 4 square Force Sensitive Resistors (FSR). FSR is a low cost sensor having sensing area of 1.75x1.75". Basically the function of these FSR is to detect any physical pressure or weight applied over them. The resistance of FSR varies upon the pressure applied on the sensing area. Stronger the force, the lower will the resistance. Hence we get the analog readings of the current passing through them when different pressures experienced by their sensing area. Although these sensors are not accurate in terms of readings but the Care-Chair only requires the relative changes in the amount of the pressure or force applied rather than the accuracy of the measure of the pressure or the force applied. Considering all these properties,each of the 4 sensors were placed at the well calculated locations on the backrest of the chair. The selected locations were determined and finalized after multiple testing with different users of different height and volume. The whole purpose behind the proper placement of the FSR was to make sure that all the four sensors must be in proper contact with the occupant so that the quality of data received must be good.

In order to receive the readings of pressure data from the FSR and collect it in digital form, Arduino or RFduino can be used. But considering the advantages of RFduino over Arduino like comparatively smaller size, wireless enabled microcontroller with BLE communication capability and low cost has made RFduino qualified as an ideal fit for Care-Chair. RFduino development kit consists of two boards (Figure 3.2), one is DIP mainboard and another is the USB shield. The USB shield combined with the DIP mainboard gets connected to the computer via USB cable or directly to the USB port and the required code from the Arduino IDE is loaded to the mainboard. In general RFduino is a Bluetooth 4.0 Low Energy module. CR2032 Lithium metal 3V

Figure 3.1. Care-Chair Force Sensitive Resistor placement on the backrest of chair

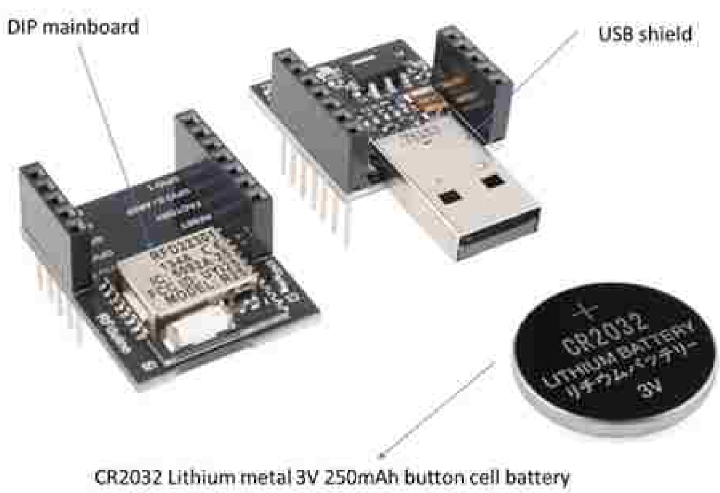

Figure 3.2. RFduino Platform used in the experiment

250mAh button cell battery (Figure 3.2) is used as the power supply for RFduino to operate and send data to the paired device using a cable or even wirelessly via Bluetooth low energy. Based on the experimental study it has been observed that using this Lithium metal 3V 250mAh button cell battery, the RFduino on the Care-Chair can operate continuously around 8 hours before running out of power. In Care-Chair, the RFduino sensor platform was kept in a small case and placed behind the backrest of the chair. All the 4 FSR are connected to the RFduino using thin wires (Figure 3.3).

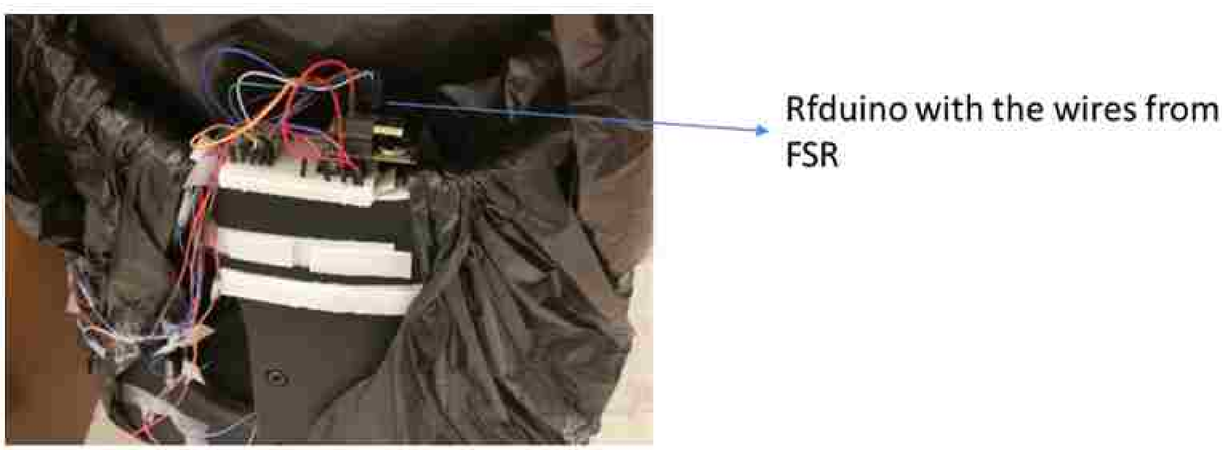

Figure 3.3. RFduino placed behind the backrest of Care-Chair

Another RFduino was connected to the computer (Figure 3.4) which can communicate with the RFduino connected to the Care-Chair using gazelle wireless protocol. In Gazelle protocol a host RFduino is allowed to communicate with 8 other devices in star topology. The device always initiates the communication and the data packets sent by the devices must be acknowledged by the host. It follows two-way communication protocol between the host and the participating devices. In the case of Care-Chair, the host RFduino is the one connected to the computer and communicating with the device RFduino connected to the chair. To note that there are different and separate codes installed on the host RFduino and device RFduino which

Figure 3.4. RFduino device connected to computer for receiving data from the slave RFduino in the chair

are meant to perform different task. The device RFduino was programmed to collect the data from the 4 FSR and transfer it to the host in packets whereas the host RFduino was programmed to collect the data which was sent from the device to the host to display as well as store it on the computer to which it was connected. The overall design of the Care-Chair system is presented in Figure 3.5. The sampling rate of data from each sensor was 10 Hz.

Figure 3.5. Overall Care-Chair system design

4. ACTIVITY SELECTION AND DATA COLLECTION

After the proper setup of the system (Care-Chair) the major challenge was to decide the list of activities which needs to be classified. The list must contain only those activities which are generally performed by the occupant during sitting position. Since only the backrest of the chair was used rather than the whole chair, so the activities must be something in which the backrest is usually involved. The main purpose of Care-Chair is to facilitate elderly population, patients at home or hospitals and people involved in more sedentary jobs like computer professionals and office workers. Considering all these factors, a list of 18 activities which a Care-Chair occupant can perform and which can reflect subtle but important information about their health was created. This list includes following activities: 1.sitting still, 2. napping, 3. looking back left, 4. looking back right, 5. nodding head side-to-side, 6. nodding head up-down, 7. Waiving hand, 8. Talking, 9. Sneezing, 10. Coughing, 11. Drinking, 12. Eating, 13. Hiccups, 14. Crying, 15. Laughing, 16. Shouting, 17. Yawning and 18. Yelling. Further all these activities were categorized into following sub-groups: Static activities: napping, sitting still Movement based activities: looking back left, looking back right, nodding head side-to-side, nodding head up-down, waiving hand User functional activities: talking, sneezing, coughing, drinking, eating, hiccups Emotion based activities: crying, laughing, shouting, yawning, yelling

The data for all the selected activities was collected from 5 motivated users. Each users were asked to perform all the activities separately. The minimum time period set for each activities was 2 minute. But few of the activities like coughing, sneezing, crying, hiccups, yelling, laughing, shouting and yawning were difficult to emulate for longer period of time. So the users were asked to perform as long they are feeling comfortable in doing so. All these difficult activities were actually painful to emulate unless it is occurring naturally. But the dedication of all the users towards the research work and their commitment towards science was really appreciable. The users tried to perform all these activities as naturally as they can. During emulating the activities like coughing, sneezing and yawning it was observed that eventually they end up getting it naturally. Before emulating the laughing activity they were shown their favorite comedy show or reminded them some funny moments so that the laugh can come naturally. For shouting activity, the users were told to argue aggressively and loudly with someone over any controversial topic. Yelling was performed by repeatedly and loudly calling someone for help. The difference between shouting and yelling was that during shouting there was a sudden burst of air coming out from the inside while yelling is the activity where there is a prolonged release of air pressure and stretching the duration of word pronunciation. All these practices and precautions were considered for these difficult activities to ensure the closeness to neutrality.

Other usual and easy to emulate activities like talking, sitting still, napping, looking back left, looking back right, nodding head side-to-side, nodding head up-down, waiving hand, drinking and eating were comfortably emulated by all the users. The talking activity is just like a general talk to someone with usual expressions and hand movements. Sitting still is sitting on the chair without any movement as if the user is silently listening or watching something and his back is touching the backrest. Napping is the complete relaxing position where users let their whole upper body weight including head onto the backrest of the chair. It was observed that during this activity the lower 2 pressure sensors (A1 and A4 as shown in Figure 3.1) were either not or very slightly in contact with the body of the user. During looking back right activity, user was asked to turn bit right in the sitting position and look back as if he is trying to see something placed diagonally at right-back. Similarly, during looking back left activity, user was trying to look back towards his left-back diagonal. In nodding head side-to-side activity the user simply moves his head side-by-side similar to saying no gesture. In just opposite context of saying yes the users moved their head up and down during the activity of nodding head up-down. Waiving hand is the activity where users have to waive their both hand by lifting it above their head as if they are trying to get attention from someone locating far from them. For performing the eating activity the users were given sandwiches and bag of chips and they have to eat it in their usual style. For drinking activity, a bottle of water was served to the users. All of these sedentary activities were mostly practiced by elderly persons or patients in hospitals or people involved in more sedentary jobs and keeping that in mind, the users tried their best to perform them as naturally as they can. All the activities performed by the users were video recorded with the timestamp in order to verify the collected data in case of any abnormality observed. The video recording was done only after the consent of the users.

A total of 78,333 data points were collected from the 5 users after performing all the above mentioned 18 activities. Each data points consists of 4 timestamped pressure sensor data value with ground truth data. The raw pressure data for each activity is shown in the Figures 4.1 - 4.18.

Figure 4.1. Napping raw pressure data

Figure 4.2. Sitting still raw pressure data

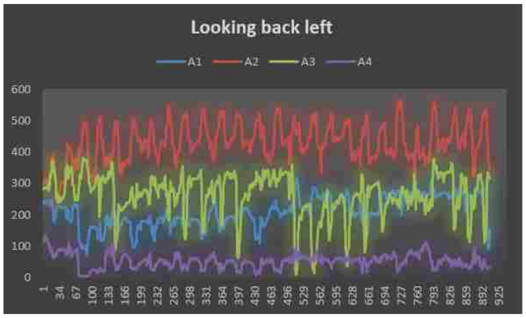

Figure 4.3. Looking back-left raw pressure data

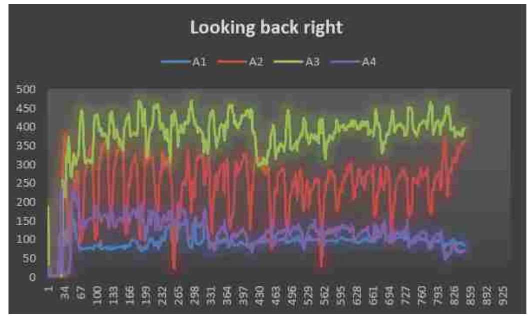

Figure 4.4. Looking back right raw pressure data

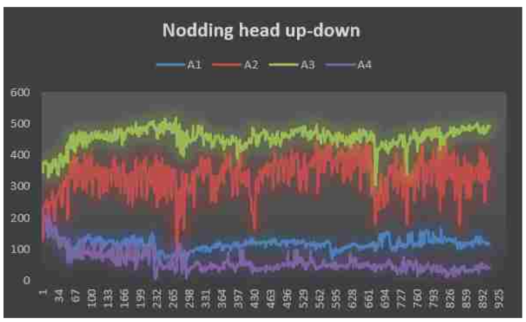

Figure 4.5. Nodding head up-down raw pressure data

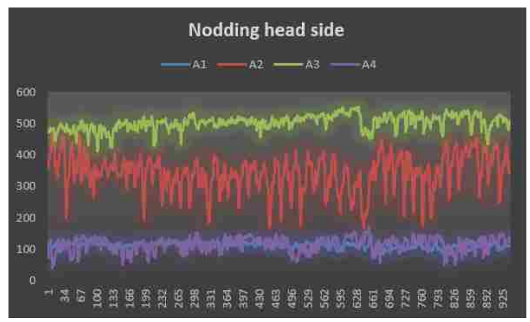

Figure 4.6. Nodding head side raw pressure data

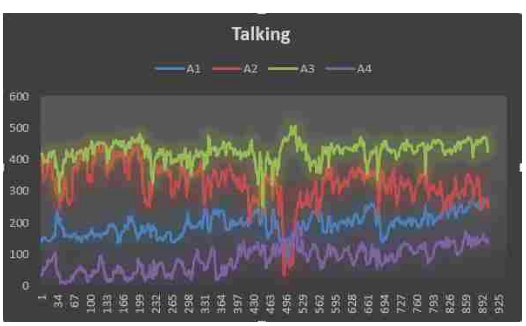

Figure 4.7. Talking raw pressure data

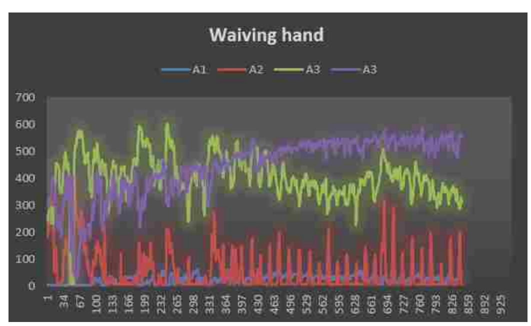

Figure 4.8. Waiving hand raw pressure data

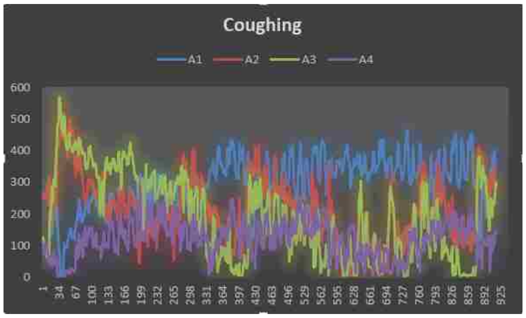

Figure 4.9. Coughing raw pressure data

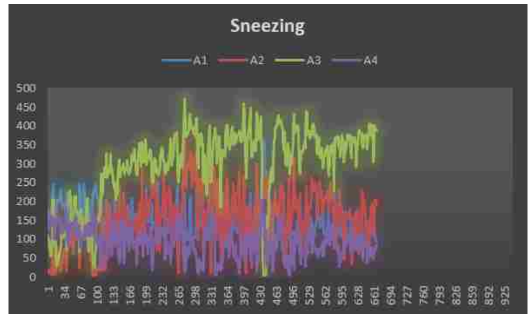

Figure 4.10. Sneezing raw pressure data

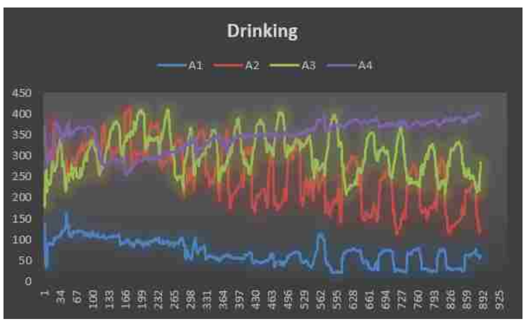

Figure 4.11. Drinking raw pressure data

Figure 4.12. Eating raw pressure data

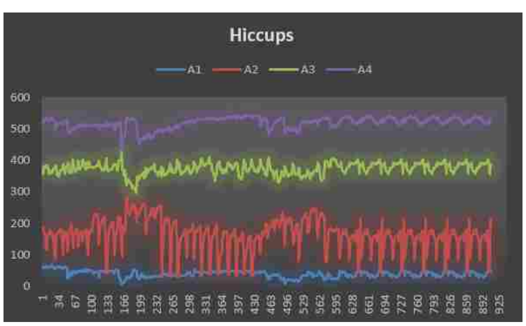

Figure 4.13. Hiccups raw pressure data

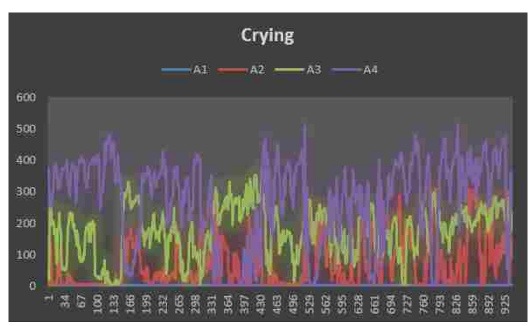

Figure 4.14. Crying raw pressure data

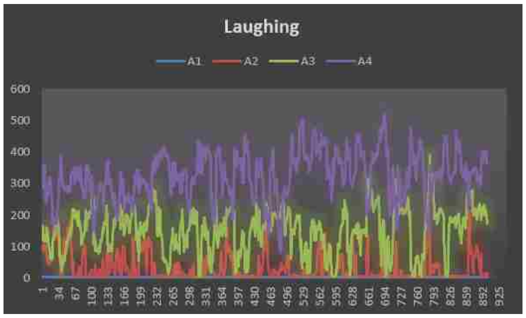

Figure 4.15. Laughing raw pressure data

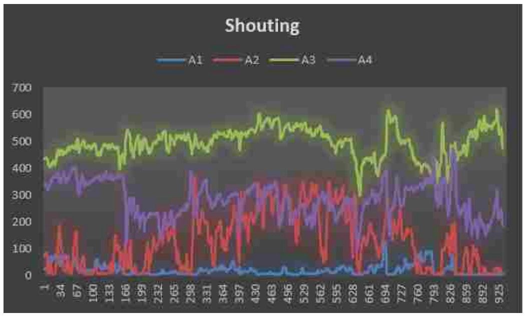

Figure 4.16. Shouting raw pressure data

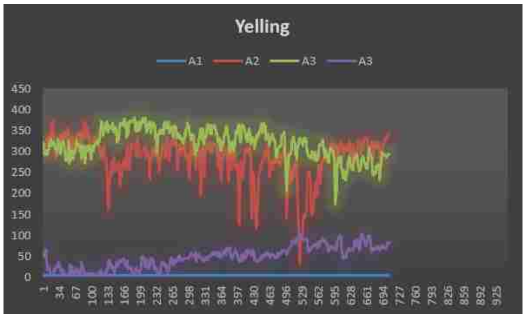

Figure 4.17. Yelling raw pressure data

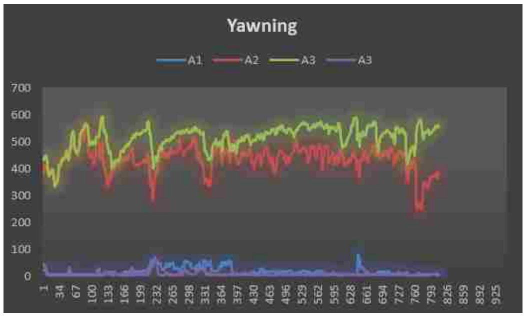

Figure 4.18. Yawning raw pressure data

5. FEATURE SELECTION AND ACTIVITY CLASSIFICATION

Feature selection is the first important step in machine learning based classification approach as it has a major contribution in creating an accurate predictive model. Basically machine learning classification is a method to estimate the functional relationship between a set of input vectors $X = x_1, x_2, x_3 \ldots x_N$ and its corresponding output Y based on their knowledge of the previous data points X_i, Y_i where i = 1 ... N and $X_i \ldots {}_N$ are vectors of reals and $Y_i \ldots {}_N$ are real numbers. It is not always necessary to use all the available features as input to estimate the output efficiently and accurately. Even a subset of those features can be sufficient to determine the output. So it is extremely important to notice that the subset of irrelevant features can lead the process to become computationally very expensive and as well as to overfitting problem. Consider a process whose computational time is $O(n^3)$ for a single prediction where n is the number of features and $n<N$. Hence adding even a single irrelevant feature for large number of predictions can drastically increase the computational time. Overfitting is the selection of any feature which cannot play any significant role in training a model and often leads to poor predictive performance. Consider a face detection system which detects human faces in a given picture using the pixels and other features of the image. Assuming the name and height of the persons used as features to define the relationship to human face can lead the system to more complex model and results erroneous predictions. Additionally, leaving or ignoring certain features which can add value to the prediction models also affects the system by giving poor classification results.

The Care-Chair system uses mean and variance of both the time domain as well as frequency domain of the original signal from a single sensor with Fast-Fourier Transformation (FFT). Hence with 4 features from a single sensor, there are total of 16 features were used for training and prediction process. These features were calculated using the data samples collected over the sliding window of 3 seconds (30 samples from each individual pressure sensors) and with 50% overlapping. This size of window for feature selection was well tested before taking into the consideration.

After the feature selection task, the major next important challenge was to determine the machine learning classifiers which can efficiently and accurately classify the activities given the set of features input. In order to find the appropriate machine learning classifier the performance of 13 machine learning classifiers were evaluated exhaustively for all the 18 activities. These are following machine learning classifiers evaluated: (1) AdaBoost, (2) Gradient Boosting Tress, (3) Bernoulli Nave Bayes, (4) Gaussian Nave Bayes, (5) Multinomial Nave Bayes, (6) Decision Tree, (7) Random Forest, (8) Extremely Randomized Trees, (9) Linear Discriminant Analysis, (10) Quadratic Discriminant Analysis, (11) Stochastic Gradient Descent, (12) Support Vector Machine and (13) K-Nearest Neighbor. All the classifiers had different execution timings as well as classification accuracy.

5.1. CLASSIFICATION PERFORMANCE

The confusion matrix generated after the classification of 18 activities using each classifiers (except) is shown in the Figures 5.1 - 5.12. The accuracy and execution time for each classifier is mentioned in the Table 5.1.

It can be seen from the Table 5.1 as well as in the Figure 5.13 that 8 out of 13 classifiers has not even reached upto 50% of accuracy. The rest of the classifiers with better accuracy percentage are K-Nearest Neighbor (68.44%) and Decision Tree Classifier (74.52%) which are less than 80% accuracy whereas the classifiers with more than 80% accuracy are Gradient Boosting Tress (83.01%), Random Forest (85.72%) and Extremely Randomized Trees (86.22%). As an obvious fact that the selection of the classifiers should be from the top performers, the other parameters which was

Table 5.1. List of classifiers with their classification accuracy and execution timings

SNo	Classifiers	Accuracy (%)	Training Time (in Sec)
1.	Stochastic Gradient Descent	6.561345	3.242098
2.	Support Vector Machine	7.657026	466.962
3.	Gaussian Nave Bayes	9.255956	1.774822
4.	Multinomial Nave Bayes	15.73449	2.446841
5.	Bernoulli Nave Bayes	16.40336	1.777273
6.	AdaBoost Classifier	26.43649	159.2569
7.	Linear Discriminant Analysis	29.62798	2.642385
8.	Quadratic Discriminant Analysis	48.06345	2.784103
9.	K-Nearest Neighbor	68.44821	3.080137
10.	Decision Tree Classifier	74.52542	4.18028
11.	Gradient Boosting Tress	83.01057	1873.449
12.	Random Forest	85.7243	22.91507
13.	Extremely Randomized Trees	86.22754	2.837102

included was the time elapsed to train the model. It can be observed from the Table 5.1 and Figure 5.14 that among the execution time of the good performers i.e Gradient Boosting Tress (1873.449 sec), Random Forest (22.91507 sec) and Extremely Randomized Trees (2.837102 sec), Extremely Randomized Trees has given the best performance with highest accuracy and lowest training time. Hence Extremely Randomized Tree classifier is the best classifier for the Care-Chair.

5.2. PERFORMANCE EVALUATION OF EXTREMELY RANDOMIZED TREES

Due to the best performance in terms of highest classification accuracy and lowest execution time, the Extremely Randomized Tree is considered as most appropriate activity classifier for Care-Chair. The selected activities were very fine grained activities and few of them were so closely related to each other that it was difficult for any classifier to distinguish them. Furthermore, this classification experiment was done with cross-user data. It means that the learning of the system was done with

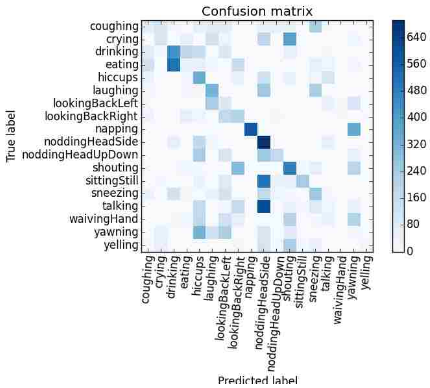

Figure 5.1. Confusion matrix of classification performance by AdaBoost

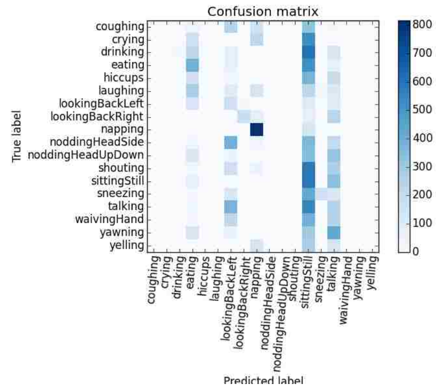

Figure 5.2. Confusion matrix of classification performance by BernoulliNB

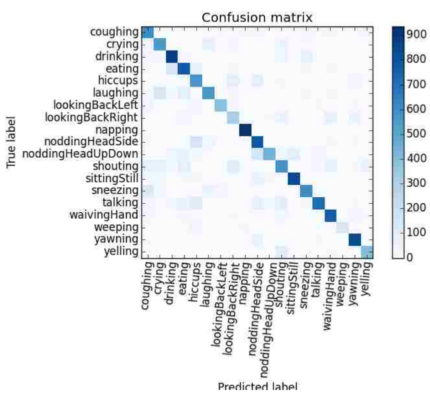

Figure 5.3. Confusion matrix of classification performance by Decision Tree Classifier

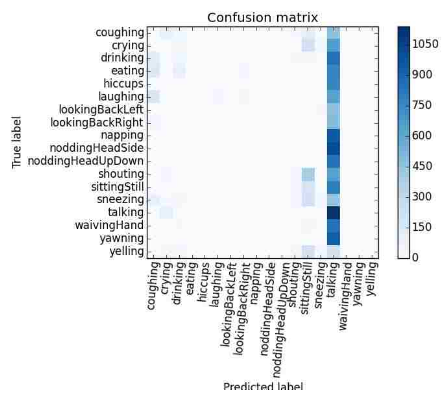

Figure 5.4. Confusion matrix of classification performance by GaussianNB Classifier

the data of some other user and then another user data was used for the classification test. It was not an easy task to classify such fine grained activities from different users because different person perform these activities in different style and different body movement. As shown in Figure 5.15, the confusion matrix generated for Extremely Randomized Tree, the y-axis represents the actual labels or ground truth labels of

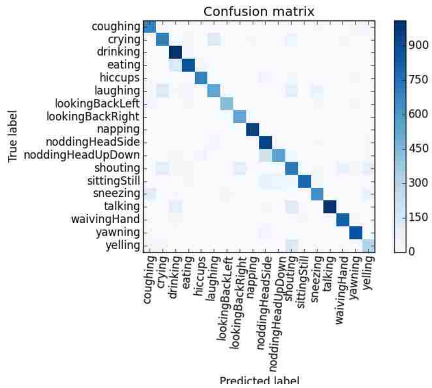

Figure 5.5. Confusion matrix of classification performance by Gradient Boosting Classifier

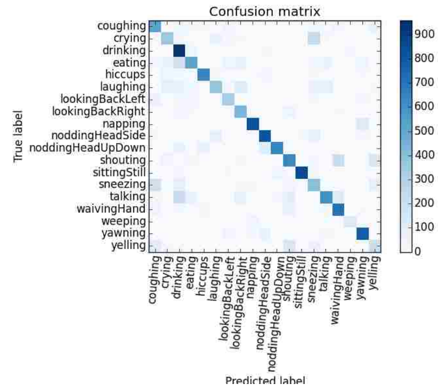

Figure 5.6. Confusion matrix of classification performance by KNeighbors Classifier

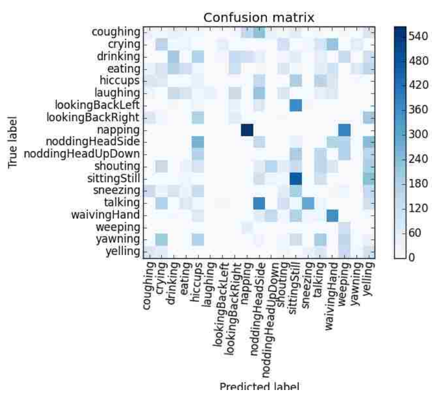

Figure 5.7. Confusion matrix of classification performance by MultinomiNB Classifier

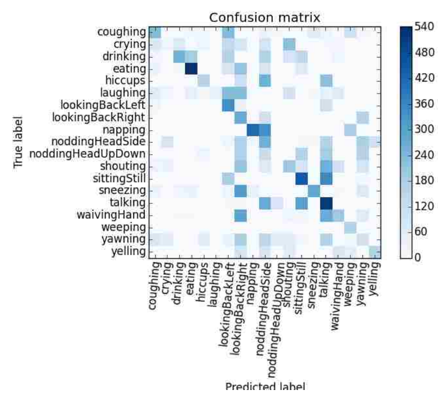

Figure 5.8. Confusion matrix of classification performance by Linear Discriminant Classifier

the all the 18 activities and the x-axis represents the predicted activities by the classifier. The thick density of color over the diagonal represents the accuracy of the classification. The higher the density of the color for a particular activity, higher is the accuracy of classification. It can be observed by the Figure 5.16 that most of the activities have higher classification accuracy. It is interesting to note that few of the activities which were misclassified as some other activities were contextually similar.

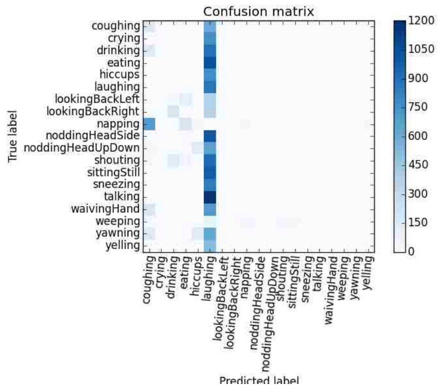

Figure 5.9. Confusion matrix of classification performance by Stochastic Gradient Classifier

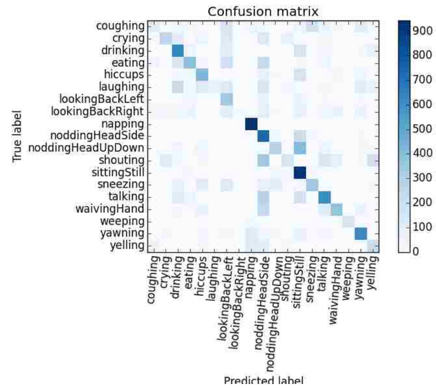

Figure 5.10. Confusion matrix of classification performance by Quadratic Discriminant Classifier

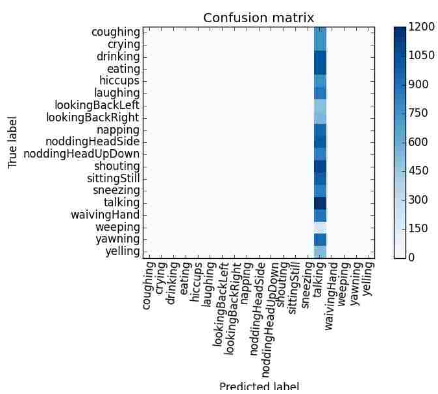

Figure 5.11. Confusion matrix of classification performance by Support Vector Machines Classifier

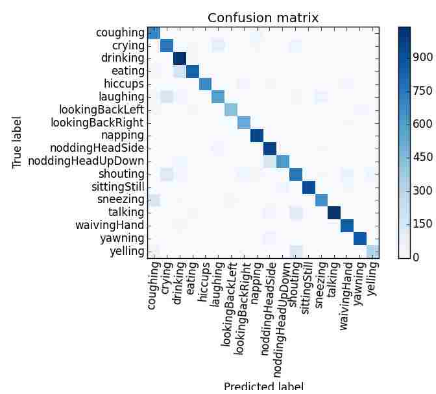

Figure 5.12. Confusion matrix of classification performance by Random Forest Classifier

For example eating was misclassified as drinking, talking and yelling were misclassified as shouting, sneezing was misclassified as coughing, sitting still was misclassified as napping, nodding head up-down was misclassified as nodding head side.

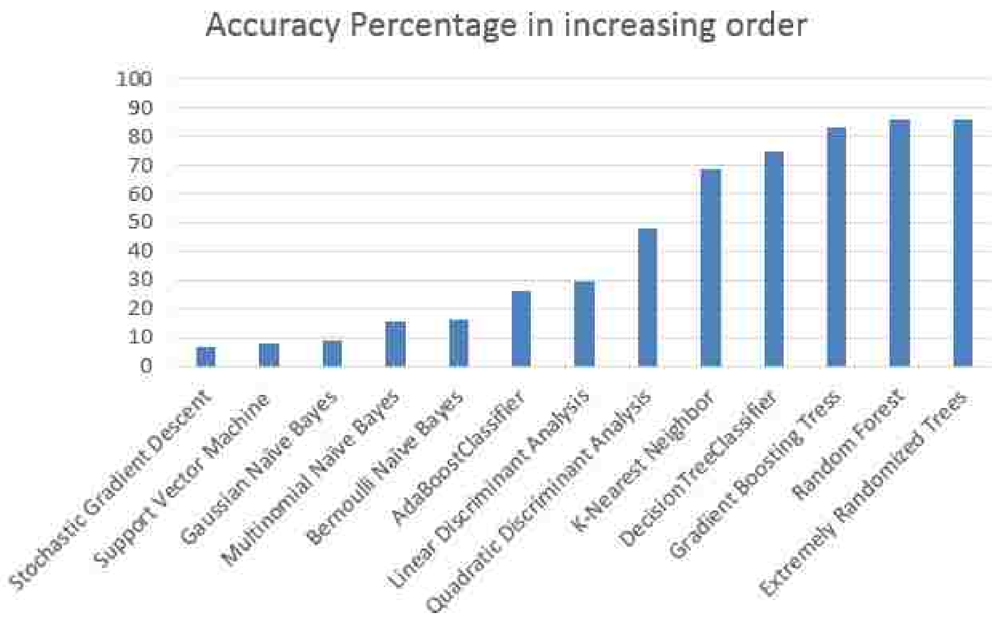

Figure 5.13. Classification accuracy of 13 machine learning classifiers

Figure 5.14. Execution timing of 13 classifiers

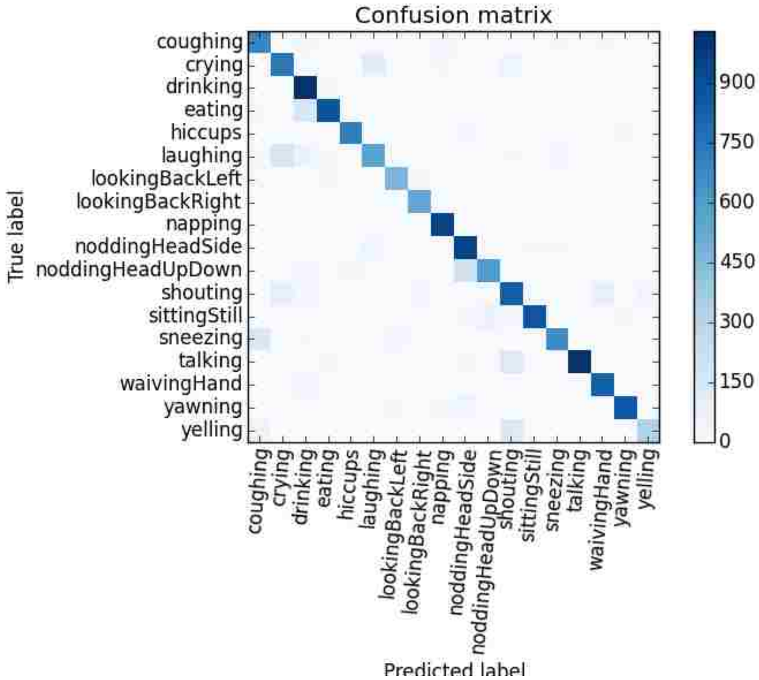

Figure 5.15. Confusion matrix of classification performance by Extremely Randomized

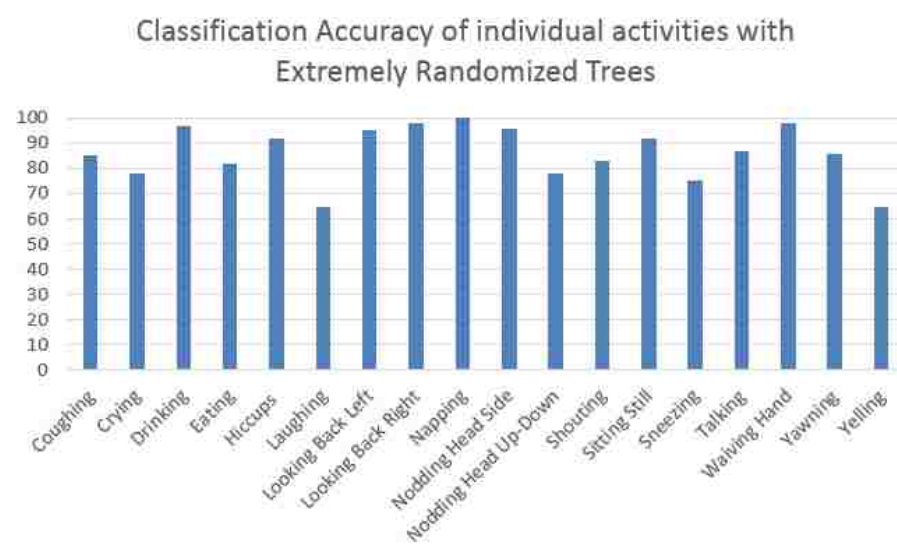

Figure 5.16. Classification Accuracy of individual activities with Extremely Randomized Trees classifier

6. BREATHING RATE DETECTION

Respiration is a biological process which involves periodic sequence of inhales and exhales. Inhaling expands the thorax region of the body due to the air intake which subsequently contracts during exhaling. The frequency of expansion and contraction during breathing can tell the breathing rate of a person. There are devices like Respiratory Belt Transducer which contains a piezo electric device and Respiration monitor belt which uses gas pressure sensors to measure the breathing rate of a person utilizing the frequency of the contraction and expansion of their thorax region during respiration. But these are devices which needs to be carried all the time tied closely to the persons body. Very few people who needs to know their breathing rate every second or minute can tolerate it on their body all the time. There is a need to frame a device which can opportunistically measure the breathing rate of the users without any human intervention.

Motivated by the work of Griffiths et al. [10], the Care-Chair was designed to calculate the breathing rate of the user in certain situations apart from activity detection. The pressure sensors mounted on the backrest rest of the Care-Chair can measure the breathing rate of the occupant. The accuracy of the calculated breathing rate depends on the absence of noise in the data. The noise here means the data generated or retrieved due to the change of force experienced by the pressure sensors resulting from the movements other than breathing.

The Care-Chair system was used to calculate the breathing rate of the occupants. The accuracy and the usability of the system to determine the breathing rate was verified using 19 users (9 male and 10 female) data. The users were asked to breathe in 3 different ways, each for 4-5 minutes. First was the slow breathing in which the users were asked to breathe comparatively slower than the normal breathing. Second is the normal breathing during which they have to do usual breathing. The third type of breathing was the fast breathing which was comparatively faster than the normal breathing. The raw data collected for fast, normal and slow breathing is shown in Figures 6-1, 6-2 and 6-3 respectively. An android application was used for collecting the ground truth data for breathing. The application was basically a user interface with a whole mobile phone screen space available for tapping. The user has to tap on the screen of the mobile phone with their finger when they complete a cycle of breathing, which is one inhale and one exhale. The tapping on the screen actually stores the time of the tapping. At the same time, the pressure data readings from all the four square force sensing resistors are collected in a computer. The sampling frequency of data was 10 Hz.

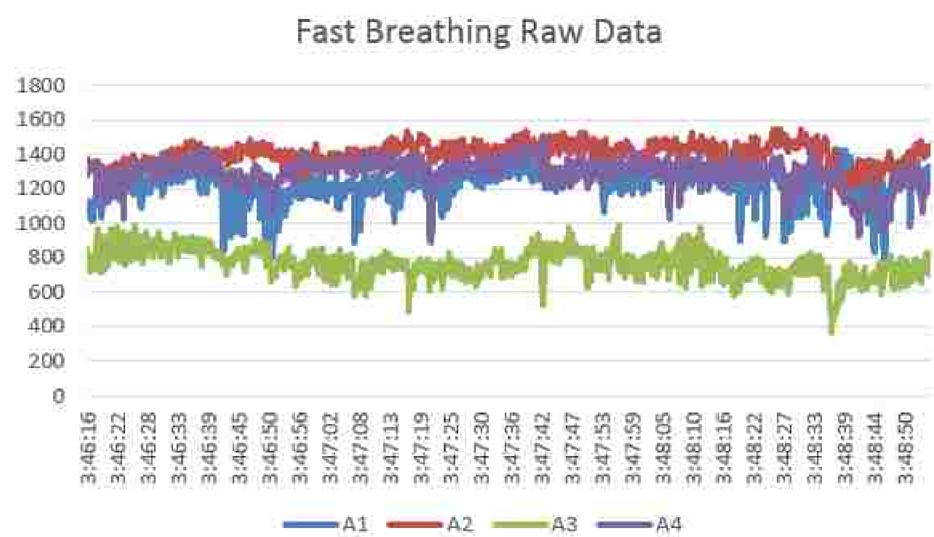

Figure 6.1. Fast Breathing Raw Data

During the experiment with 19 users few interesting outcomes for expansion and contraction were observed during breathing. People with different body structure, volume, width and height interact with the sensors on the backrest differently.

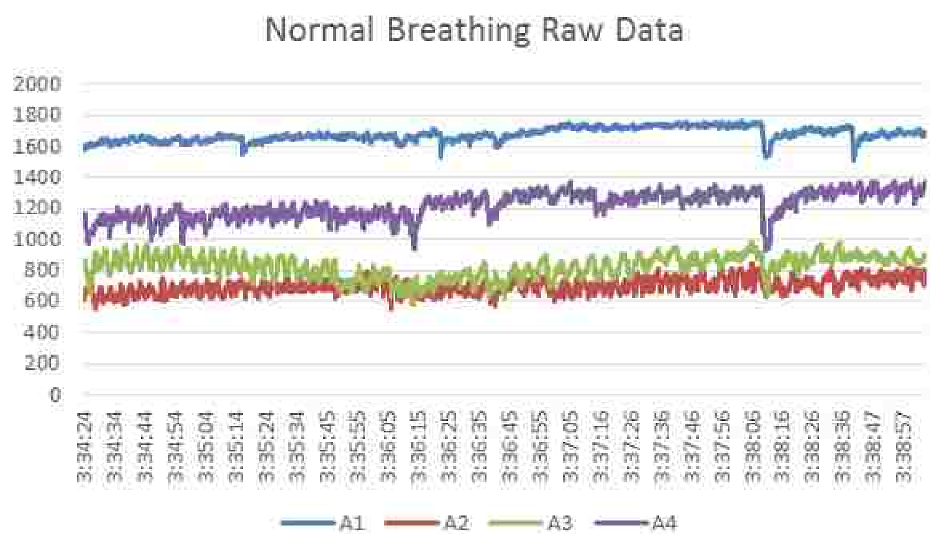

Figure 6.2. Normal Breathing Raw Data

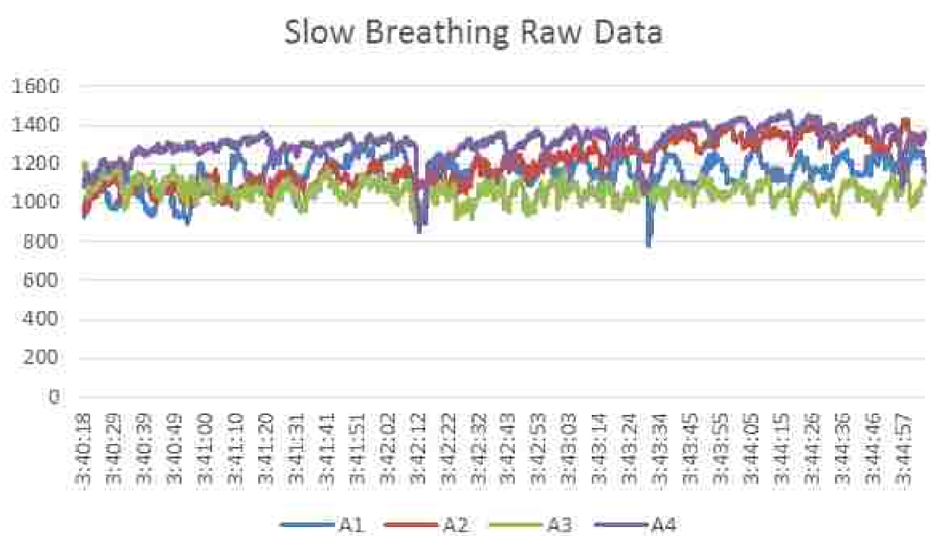

Figure 6.3. Slow Breathing Raw Data

Additionally, their breathing pattern and behavior exhibits different body movements. In the experiment it has been observed that the upper two sensors are more sensitive to breathing in comparison to the lower sensors. Depending on how the back of a person was in contact with the sensors, it was determined whether the expansion or contraction will exert force on the sensors. If a persons back was perfectly touching the upper two sensors in a normal sitting situation then inhaling was releasing the force from the sensors as the body raised upwards due to volume increase. Again the body will retain back the position on the sensors while exhaling. But the reverse will happen when the sensors are not in well contact with the body in the normal sitting situation. These observation does not affect the breathing rate calculation as it is based on the pressure gradient, not the exact pressure readings. Care-Chair will work efficiently even if the occupant is in contact with at-least one sensor.

6.1. BREATHING RATE CALCULATION

Each user dataset consists of four columns of pressure readings, each from 4 square force sensing resistors separately. The data was collected with the sampling frequency of 10 Hz. Each sensor data is divided into multiple files of 30 seconds data. Then autocorrelation was applied on the each of sensor data in the files and calculated the breathing rate separately. Autocorrelation is basically a signal processing tool where a signal correlates with itself by overlaying its own different timed lagged signals upon the original signal to find a pattern. The delay or lag was varied from 0.5 seconds (i.e. 5 samples) to 30 seconds (i.e. 300 samples). Autocorrelation was calculated with each of these lagged signals (with the original signal). The lag-length giving the first peak was selected to calculate the time period of the signal when it gets the first peak. The inverse of this time period was then the breathing rate calculated for that segment. The autocorrelation graph generated for fast, normal and slow breathing is shown in Figures 6-4, 6-5 and 6-6 respectively. The y-axis of the graph plots represent different lag-lengths and from there a specific lag-length is selected from the point where the first peak is found.

$$Assume, lag - time = \tau; lag - length = \alpha; sampling - rate = \gamma$$

$$So, \tau = \frac{\alpha}{\gamma}$$

$$Breathing\ rate\ per\ minute = 60 * \frac{1}{\tau}$$

As an example, consider the first peak of the autocorrelation determined from fast breathing (Figure 6.1) which has got the first peak at lag-value of 15 (calculated using matlab) and the data was collected with a sampling rate of 10. Hence, $\alpha = 15$ and $\gamma = 10$. So $\tau = 1.5$ and hence the breathing rate is $\frac{60}{\tau}$ i.e 40.

The breathing rate calculated from each 30 seconds data file was averaged to determine the breathing rate from each sensors separately. Once the separate breathing rates were calculated from all the 4 sensors then again they were averaged to calculate the final breathing rate. The ground truth breathing rate was calculated for every 30 seconds and then averaged to determine the overall ground truth breathing rate. Figures 6-7, 6-8 and 6-9 is showing the slow, normal and fast breathing rates of 19 users (10 female and 9 males) with their ground truth.

6.2. MOBILE APPLICATION

Using the above principle, an iphone application was created which can determine the real-time breathing rate of the occupant. The readings of pressure data from the rfduino was transferred to the mobile application via Bluetooth Low Energy. The application internally does all the required data processing as discussed above. The application consists of GUI (Graphics user interface) (Figure 6.10) showing the image of the chair with 4 square shapes drawn on its backrest indicating 4 sensors. They represents the sensors in the same sequence as in reality. The color of the square

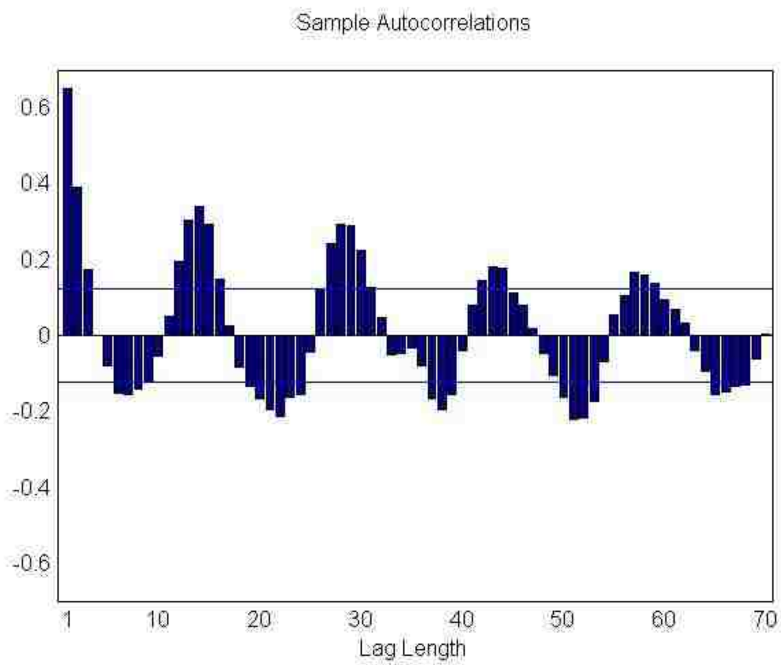

Figure 6.4. Autocorrelation for fast breathing

boxes are initially white when no force is applied. Each sensor displays a specific color during the change in their resistance. The intensity of the force applied on the sensors can be seen with the area covered by the colors. Additionally, the raw data from each sensor is displayed in numbers as well as using line graph in their corresponding color. Control mechanisms are provided to control the display of each line graph as per the user requirement. Finally the application displays the breathing rate of the occupant at the bottom of the screen. The application is compatible with both mobile phone as well as iPad.

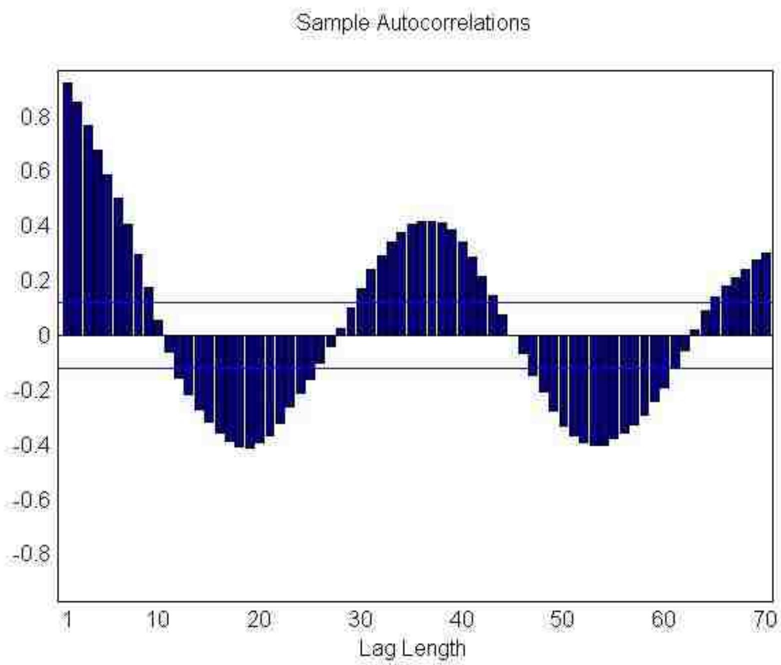

Figure 6.5. Autocorrelation for normal breathing

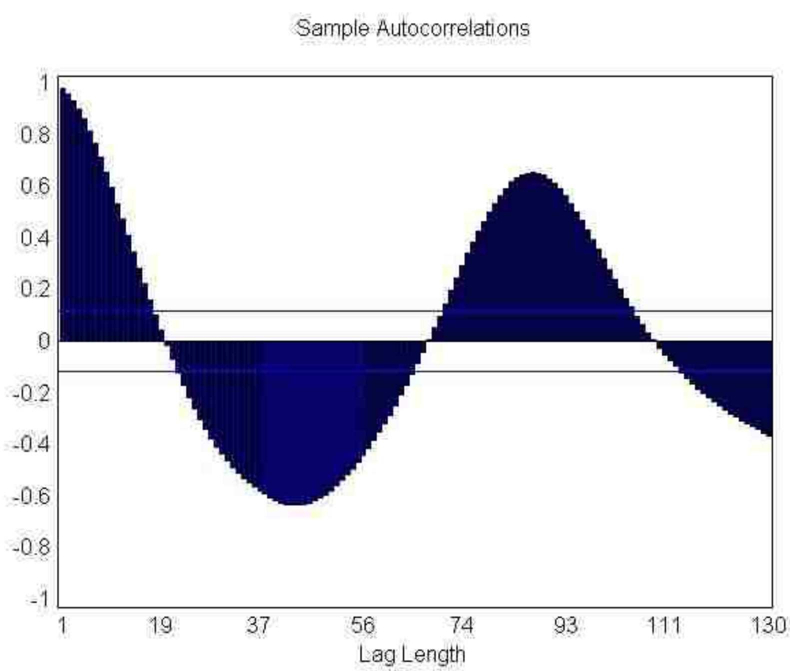

Figure 6.6. Autocorrelation for slow breathing

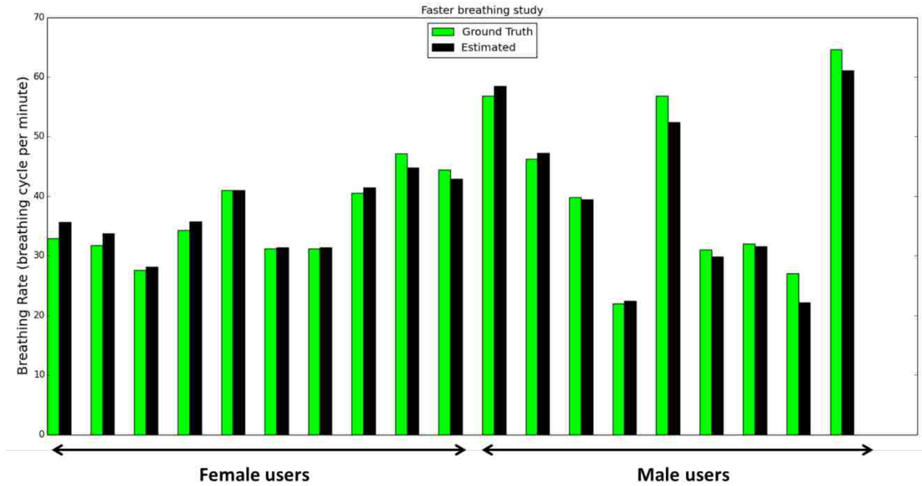

Figure 6.7. Fast breathing rates of 19 users (10 female and 9 males) and their comparisons with ground truth breathing rates collected during the experiment

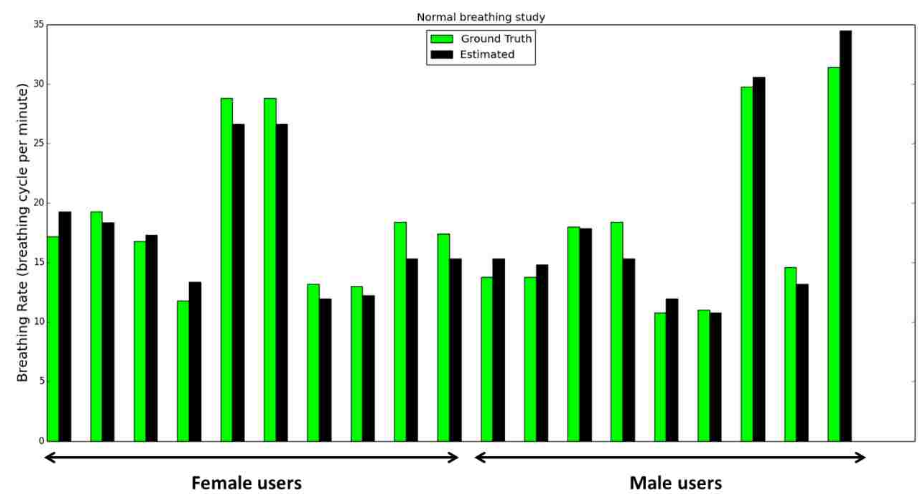

Figure 6.8. Normal breathing rates of 19 users (10 female and 9 males) and their comparisons with ground truth breathing rates collected during the experiment

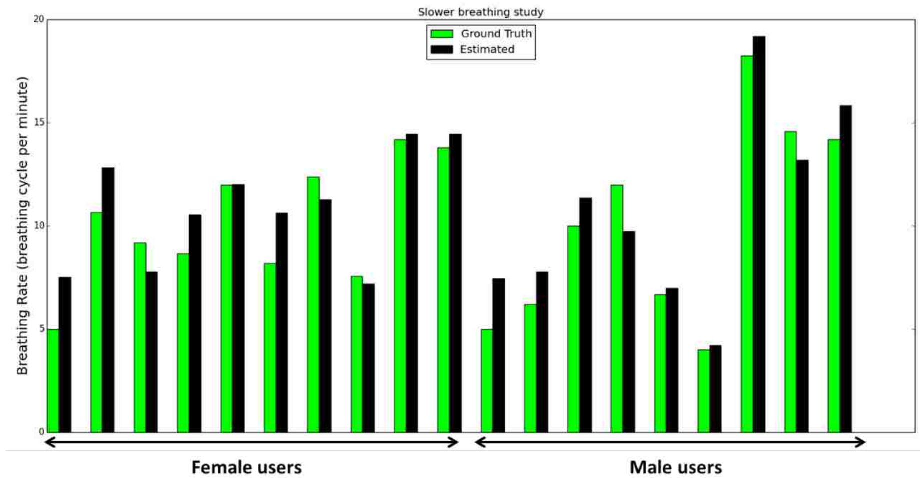

Figure 6.9. Slow breathing rates of 19 users (10 female and 9 males) and their comparisons with ground truth breathing rates collected during the experiment

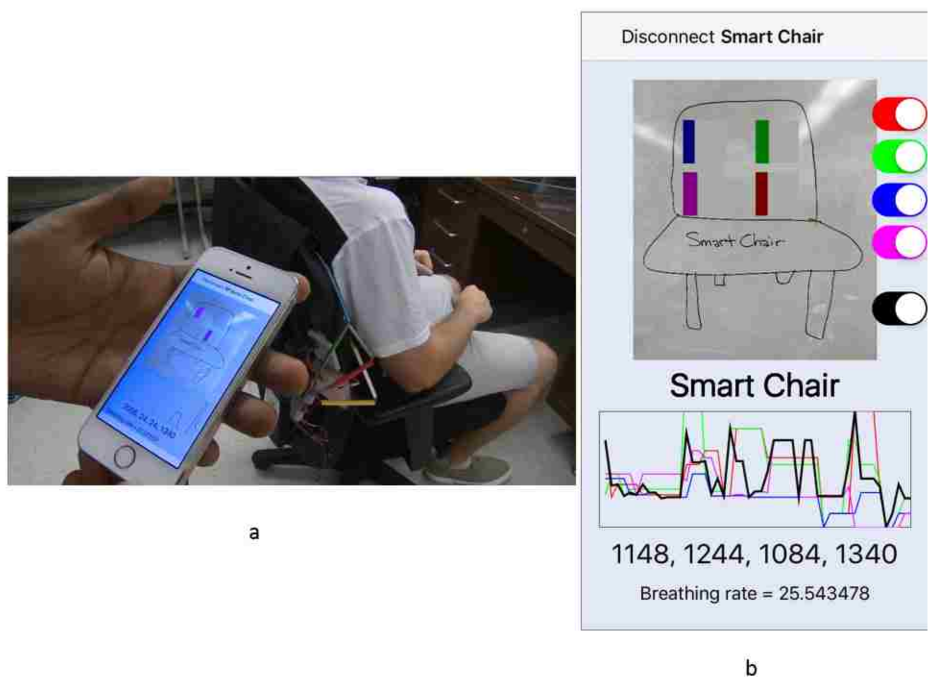

Figure 6.10. iOS Mobile application for breathing rate detection in real time. a. Application calculating the breathing rate of the user sitting on the chair b. Screen shot of the application during breathing rate detection

7. WHOLE DAY STUDY ANALYSIS

As the part of the performance evaluation for the use of Care-Chair in the wild (uncontrolled environment), 1 user was asked to sit on Care-Chair during their working hours for whole day. He was instructed to follow his daily natural schedule without paying any attention to the evaluation process. A video camera was placed near the chair covering enough space to avoid the chair going out the coverage area. The timestamped video recording was done to collect the ground truth data for verifying the classifiers output. User was free to leave the chair unoccupied for some time as per his need and requirement. Snacks and lunch was provided in the beginning of the day so that they can have them according to their convenience. In addition to that they had the facility of coffee machine and cold drinks available in the room to serve themselves whenever they are needed.

The data was collected for the whole day (almost 8 hours) and then Extremely Randomized Tree classifier was applied over the collected data which led to interesting results. The Figure 7.1 shows the activities classified by ERT performed by the user at different timestamps. In the whole day evaluation one activity called nobody sitting was included in the activity list in order to identify the moment when the user leaves the chair for any reason. All the 19 activities are represented on y-axis and their corresponding timestamp is represented on the x-axis. The activities on the y-axis are represented in numbers and their corresponding activity is given the Table 7.1 provided below the figure. The sequence is basically starting from the group of static activities, following movement activities, then functional activities and lastly emotional activities. The purpose to follow this sequence is to distinguish and better visualize the least practiced activity from frequently occurring activities. The high density near to bottom of the graph shows the more natural activities has occurred regularly. The activities with similar body movements like napping and sitting still; coughing, laughing and swinging on the chair backrest were difficult to differentiate. In an interesting observation it has been found that few activities like typing, lifting hands till face, finger combing which are not included in the activity list are classified as eating or drinking. The uniformly absence of peaks in the graph from time 14:39 to 15:27 shows the chair was unoccupied during that interval. When this was cross verified with the user as well as the recorded video, it was found the user went to attend the class during that period of time. The similar level of peaks all through the graph displays the absence of the occupant. The absence of comparatively higher density of lines at the upper level of the graph signifies less emotional activities like shouting, weeping and yelling. The presence of coughing activity during most of time is actually due to the usual movement of the user which are misclassified as coughing. The overall classification result when compared to the ground truth data was good and convincing.

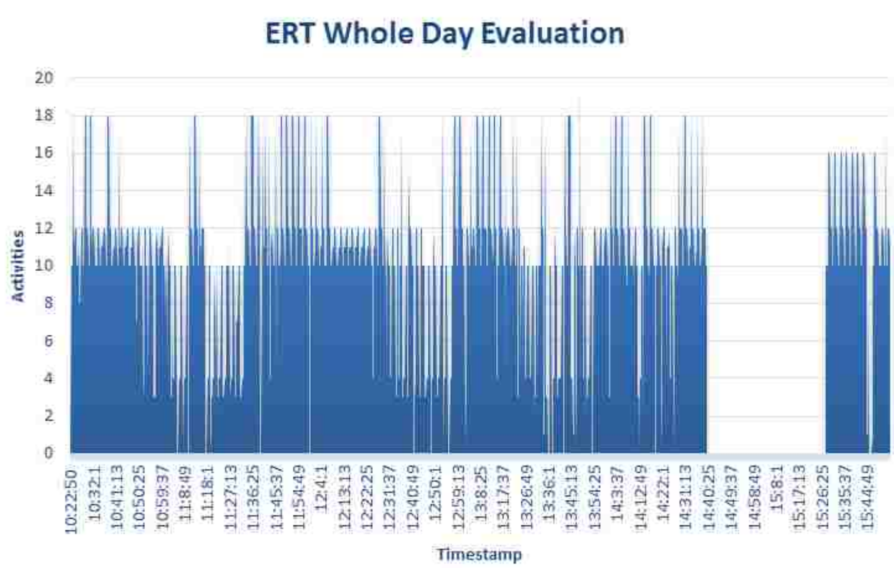

Figure 7.1. Activity classification using Extremely Randomized Tress classifier on the data collected during the 8 hours of study

Table 7.1. Reference for the activities for the numbers given the Figure 7.1

Sequence Number	Activity
0	Nobody Sitting
1	Napping
2	Sitting Still
3	Looking back left
4	Looking back right
5	Nodding head side-to-side
6	Nodding head up-down
7	Waving hand
8	Talking
9	Sneezing
10	Coughing
11	Drinking
12	Eating
13	Hiccups
14	Crying
15	Laughing
16	Shouting
17	Yawning
18	Yelling

8. CONCLUSION

The purpose of Care-Chair system design is to help the users, especially the elderly people, patients in home and hospitals and the people involve in more sedentary activities to keep track of their daily activities. It can opportunistically collect data from the occupant without any persons intervention and capable of detecting and classifying 18 different fine grained activities. The system was tested with the data of 5 users and successfully classified all the 18 activities with 86.22% of accuracy. The daily activity knowledge of a person can reveal very subtle and important information about the health condition. It reduces the overhead of wearing certain wearable health sensor which can make people uncomfortable and unfocused during their daily important activities. The Care-Chair System design is quite affordable and user friendly. It consists of just 4 FSR (Force Sensitive Resistor) mounted at the backrest of a chair which are connected with RFduino through wires. All the communication and data collection can be done via Bluetooth and Gazell wireless protocol. This makes the system looks very simple and natural. Care-Chair is also capable of measuring the breathing rate of the occupant with great accuracy. The breathing rates of 19 users (10 female and 9 male) calculated using Care-Chair produces nearly precise results close to the ground truth. Finally the system was evaluated during a day long study in uncontrolled environment with a single user. With minor misclassification due to lack of certain unspecified activities in training list and few inter-contextual misclassification like coughing as sneezing or talking as shouting, the overall classification was decent. But it cannot be denied that the system can be improved by shifting from supervised machine learning classifier to semi-supervised machine learning classifier which the future scope of Care-Chair.

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