Machine Learning Algorithms for Posture Identification of Obstructive Sleep Apnea Patients using IoT Solutions

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Abstract—Sleep apnea is a serious sleep disorder in which individuals breathing repeatedly stops and starts. Even after the continuous sleep of 6-8 hours, person feels fatigue and tiredness. This disorder turns even more serious if the person has history of heart problem. The symptoms of sleep apnea are snoring, fatigue, and somnolence, while the main types of sleep apnea are: obstructive sleep apnea, central sleep apnea and complex sleep apnea. Among these obstructive sleep apnea (OSA) is most frequent and can be treated by correct sleeping posture. Research has proved that a change in in-bed posture plays vital role for OSA. In this research we used data of two separate experiments from thirteen healthy subjects in different sleeping postures using two commercially available internet of thing (IoT) based pressure mats. On this data we employed machine learning based supervised learning algorithms for posture identification. This monitoring system may help sleep apnea patients and caregivers to be alerted of improper postures in timely manner and helps in identifying sleeping style of each patient.

Keywords—internet of things, pressure sensor mats, sleep apnea, machine learning.

I. INTRODUCTION

Sleep has many benefits on human body. It heals it and recovers energy. It is also considered as a proven diagnostic indicator for diverse medical conditions [1]. Around the globe, over 100 million people suffer from sleep apnea [2]. Americans are in the thick of a sleep epidemic. In US around 50-70 million adults are facing sleep disorder and one of the most prevalent is OSA. Also 175 million Europeans are affected by this chronic condition in breathing during sleep. The main afflict is that 75-80% of cases remained undiagnosed. The reason behind unidentified is expenses and practical limitations of whole night polysomnography (PSG) in sleep labs where practitioners works for over night. This sleep apnea turns to biggest threat for the people who goes through heart problems. Patients sleeping on supine posture can have issues like heart disease, which may eventually become the reason of death. In [3, 4] it has been verified that QT interval variability is intensity associated with heart rate (HR) variability. HR variability is affected by certain mechanisms together with the sympathethic and parasympathetic systems, and a decrease in HR variability has been shown to be correlated with serious cardiac mortality and sudden death in patients with heart disease as well as healthy controls. Similarly authors in [5] suggested that patients suffering from some respiratory conditions should ignore supine position. Another research in [6] explained that the severity and irregularity of respiratory events in patients with OSA are elevated in supine posture as compared to lateral recumbent posture because of the effect of posture on upper airway shape and size.

OSA patients could be divided into positional and non-positional patients [7]. A positional patients analyse reveals the fact that most of their breathing irregularity is caused by sleeping in supine position. Sleeping in lateral positions significantly reduce the number of hypopneas and apneas. The main objective of this research is to monitor sleeping postures of participants using IoT based pressure mats. The prime goal is to avoid supine sleep positive using objective measurements.

II. AVAILABLE SYSTEMS FOR MONITORING OF SLEEPING POSTURES

With continuous advances in healthcare system and medical technologies there are numerous available posture detection and monitoring systems. The researchers in [8] conducted experiments to prove that changes in sleep posture improve OSA. They used nasal continuous positive airway pressure (nCPAP) mask to measure upper airway closing pressure (UACP) and upper airway opening pressure (UAOP) and implemented ANOVA (analysis of variance) for statistical comparisons. The result shows that in case of severe OSA patients, the lateral positioning improves upper airway stability during sleep. In [9] a system is proposed for analyzing postures and subjects using pressure sensing mats.

The experiments used deep learning technique for subject identification in three common postures by extracting statistical features from pressure distribution. In [10] the
authors introduced a light and small wireless sleep activity monitoring system, the postures and change in posture were detected using tri-axial accelerometer. In [11, 12] OSA is diagnosed using electrocardiogram (ECG) signals and the system can be used as a basis for future development of a tool for OSA screening. As previously discussed, the sleeping postures are used in a number of medical applications, one of them being pressure ulcer. In [13] lying postures are classified for pressure ulcer prevention. In [14] a pressure sensitive bedsheets designed for obstructive sleep posture monitoring with an accuracy of 83%. The study from [15] used kurtosis and skewness estimation, principal component analysis (PCA) and support vector machine (SVM) for posture classification with the help of pressure sensitive mattress in order to also avoid pressure ulcers. As state of art, [16] introduced a supervised learning approach on data collected beforehand to build a model for long term sleep monitoring application. Hence, there is a wide range of IoT based monitoring systems available in the market.

Internet of things (IoT) is a generic term to denote objects connected to each other and exchanging information from real-world i.e. medical field. A typical IoT system architecture can be divided into three tiers of sub-architectures: the application layer in which the data is processed and the service is given to the main user, the transmission layer for remote communication and the perception layer where acquisition, processing and local communication are proceeded through wireless sensor networks (WSNs). In the context of IoTs, there have been numerous research studies on sleep apnea analysis with sleep postures. But most of these systems are generally larger, sophisticated and complex. Most of these systems require to wear or to attach the system to the human body. There is a need to concentrate and miniaturize all the sensing and hardware related technologies and a quick system to alert caregivers about the sleeping posture of patients. Hence the main objective of this research is to introduce an intelligent, small and cost effective IoT based system for monitoring sleep activity of sleep apnea patients.

Our study is divided into three sections. Section III addresses the data setup and collection from participants, section IV illustrates the basic methodology we adapted and sections V and VI show the main results and future work.

### III. DATA SETUP

#### A. Data Collection Details

The data we used for sleep posture monitoring is available on the Physionet website [17]. Physionet is famous for a larger collection of biomedical signals from patients and healthy subjects. As far from our research, PmatData is the first publicly-available dataset of pressure sensor data which includes various sleeping postures. The data was collected under IRB approval at the University of Texas at Dallas [18] from thirteen participants in different postures. Informed consents were signed by all individuals before data collection and all agreed on anonymous publication of their data for future research.

#### B. Participants

A diverse number of participants has been chosen as controls subjects to make the dataset useful for other researchers. All the 13 participants in study were healthy with no history of sleeping problems. The details of all participants are given in Table I. The subjects participated in two types of experiments.

| Index | Age | Height in cm | Weight in kg |
|-------|-----|--------------|--------------|
| 1     | 19  | 175          | 87           |
| 2     | 23  | 183          | 85           |
| 3     | 23  | 183          | 100          |
| 4     | 24  | 177          | 70           |
| 5     | 24  | 172          | 66           |
| 6     | 26  | 169          | 83           |
| 7     | 27  | 179          | 96           |
| 8     | 27  | 186          | 63           |
| 9     | 30  | 174          | 74           |
| 10    | 30  | 174          | 79           |
| 11    | 30  | 176          | 91           |
| 12    | 33  | 170          | 78           |
| 13    | 34  | 174          | 74           |

#### C. Materials and Experiments

Numerous types of pressure mattresses and bedsheets are available in the market with thousands of force and pressure sensors. The data we used in our study was collected using Vista Medical FSA SoftFlex 2048 and Vista Medical Boditrak BT3510 which are Force Sensitive Application (FSA) pressure mapping mattresses. In experiment 1, the data is collected from 13 participants using Vista Medical FSA SoftFlex 2048. The size of mattress is $32'' \times 64''$ with each sensor is 1 inch apart. The data is collected at sampling rate of 1 Hz. While experiment 2 data is collected using Vista Medical Boditrak BT3510. The size of pressure mat used is $27'' \times 64''$. The data was collected at sampling rate of 1 Hz.

#### IV. METHODOLOGY

In this study, we focused on in-bed posture detection for sleep apnea patients using pressure sensors data signals. The block diagram of the overall methodology implemented in this research study is shown in Figure 1. Initially the data collected from pressure mats is pre-processed and filtration is performed to only keep the data which is relevant for analysis. We removed unnecessary data such as the zero-values. Later we performed correlation between the sensors data (variables in table) to see the relationship between the samples we collected. After this we labelled our data in form of classes and performed classification using machine learning algorithms. The final detection and monitoring results can be directly exported to provide an alert.
A. Experiment I

In experiment I, the pressure mat is designed of total 2048 sensor points with a scan rate of 3072 sensors/second. These sensors are equally distributed across 32×64 mat with each sensor being almost 1 inch apart. The sampling frequency is 1 Hz and counts the pressure between 0 to 100 mmHg as in [19]. In experiment I, five standard postures as in [20] were collected for all 13 individuals as shown in Figure 2. In [14] study the most common postures of 1000 participants were recognized. According to their results, the right and left fetus sleeping position are the most common at around 41%. The other side lying posture or yearner position i.e. with straight legs in left or right side accounts for 28% and finally the supine posture about 8%. Therefore we labeled the collected data into five standard and common postures. First of all, we prepared the dataset for the first experiment in which we made a single file for each posture of all 13 participants and then merged them into one file for further posture detection and classification, results of which are shown in Table II.

For classifying the standard posture from the labeled data, we used classification learner app of MATLAB [21]. We used multiple machine learning algorithms for detection and most of them performed very well. The weighted KNN and the linear classifier gave promising results with accuracy of 98.7%. The results of classified model is illustrated in the form of confusion matrix, receiver operating characteristics (ROC) curves and parallel coordinates plots. The confusion matrix in Figure 3 shows how currently the selected KNN classifier has performed. It determines where the model has predicted poorly. If we look on the plot (a), the rows show the true class and the columns show the predicted class. We have used 5 fold cross validation. The diagonals emphasize where the true class and the predicted class match. The blue boxes in diagonal depict that the classifier has made the classification and the observations of this true class are classified correctly. Plot (b) shows the true positive rates (TPRs) and the false negative rates (FNR). TPR is the proportion of correctly classified observations per a true class and FNR is the proportion of incorrectly classified observations per true class. The last two columns on the right depict the summarize per true class. Finally, plot (c) shows the true positive rates (TPRs) and the false negative rates (FNR). TPR is the proportion of correctly classified observations per predicted class and the false discovery rates (FDR) which is the proportion of incorrectly predicted points in each class. Figure 4 shows the parallel coordinate plots of the trained model. Figure (a) presents the model predictions in range scaling and figure (b) emphasizes the model prediction in standardized scaling. The cross in the plots represents incorrect predictions.

B. Experiment II

In the second part of the experiment I, we detected the postures of each single participant and the classifier showed promising result as it can be seen in table III. This proves that we can also identify each type of postures of each individual.

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TABLE II. RESULTS OF POSTURE DETECTION

| Index | Algorithm   | Accuracy |
|-------|-------------|----------|
| 1     | Fine Tree   | 98.3     |
| 2     | Medium Tree | 98.2     |
| 3     | Coarse Tree | 77.5     |
| 4     | Fine KNN    | 98.6     |
| 5     | Medium KNN  | 98.5     |
| 6     | Coarse KNN  | 97.5     |
| 7     | Cosine KNN  | 98.5     |
| 8     | Cubic KNN   | 98.4     |
| 9     | Weighted KNN| 98.7     |
| 10    | Linear SVM  | 98.7     |
| 11    | Quadratic SVM| 98.1    |
| 12    | Cubic SVM   | 94.1     |
| 13    | Fine Guassian| 98.2    |
| 14    | Medium Guassian| 98.1  |
| 15    | Coarse Guassian| 97.7   |
V. CONCLUSION

In conclusion, tracking in-bed postures can be a healthy exercise to avoid certain kind of illnesses, especially in case of sleep apnea patients. This research dealt with different postures and highlighted the most common posture associated with multiple health issues i.e. sleeping on a supine position. This proves that with slight improvisation in sleeping patterns, one can avoid several health risks. In this research, the available data have been labeled and after pre-processing, we ran it through multiple algorithms with the help of classification learner app in MATLAB in order to monitor sleep postures successfully with high accuracy rates. Based on the designed classifiers, we could differentiate IoT based pressure sensor mattresses and found that monitoring of sleeping postures using air mattresses may not provide promising results. Hence, the type of mattress does matter in detecting postures.

VI. FUTURE WORK

In future, we intend to work on algorithms based on unsupervised learning with the help of other platforms like Python. We also aim to build a system which not only can monitor the sleeping postures but also is capable of tracking records of heart rates to avoid the risk of heart failures while sleeping. Furthermore, we are much interested to base our whole system on IoT to obtain the best results remotely.

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(a) The number of observations of a model

(b) True Positive Rates (TPRs) and False Negative Rates (FNRs) of the predicted model

(c) Positive Productive Values (PPV) and False Discovery Rates (FDRs) of the predicted model

Fig. 3. Confusion Matrix
### TABLE III. ACCURACY OF ALL MACHINE LEARNING CLASSIFIERS FOR POSTURE DETECTION OF EACH SUBJECT

| Subject | Coarse | Gaussian | Medium | Fine |
|---------|--------|----------|--------|------|
| S1      | 97.1%  | 96.1%    | 97.7%  | 97.8%|
| S2      | 97.6%  | 96.2%    | 97.8%  | 97.3%|
| S3      | 97.5%  | 97.3%    | 97.7%  | 97.6%|
| S4      | 97.4%  | 96.5%    | 97.6%  | 97.7%|
| S5      | 97.3%  | 95.8%    | 97.5%  | 97.7%|
| S6      | 97.2%  | 95.4%    | 97.4%  | 97.5%|
| S7      | 97.1%  | 94.9%    | 97.3%  | 97.4%|
| S8      | 97.5%  | 95.3%    | 97.6%  | 97.7%|
| S9      | 97.1%  | 94.7%    | 97.3%  | 97.4%|
| S10     | 97.3%  | 95.1%    | 97.6%  | 97.7%|
| S11     | 97.2%  | 94.9%    | 97.5%  | 97.7%|
| S12     | 97.1%  | 94.5%    | 97.4%  | 97.5%|
| S13     | 97.2%  | 93.8%    | 97.5%  | 97.7%|

(a) Predicted model in range scaling

(b) Predicted model in standardized scaling

Fig. 4. Parallel coordinate plots

### TABLE IV. RESULTS OF POSTURE DETECTION USING AIR MATTRESS

| Index | Algorithm | Accuracy |
|-------|-----------|----------|
| 1     | Fine Tree | 51.2%    |
| 2     | Medium Tree | 44.1%   |
| 3     | Coarse Tree | 37.7%   |
| 4     | Fine KNN | 71.1%    |
| 5     | Medium KNN | 60.6%   |
| 6     | Coarse KNN | 51.4%   |
| 7     | Cosine KNN | 60.7%   |
| 8     | Cube KNN | 58.6%    |
| 9     | Weighted KNN | 70.6%  |
| 10    | Linear SVM | 40.1%   |
| 11    | Quadratic SVM | 39.4%  |
| 12    | Cube SVM | 68.2%    |
| 13    | Fine Guassian | 63.3%   |
| 14    | Medium Guassian | 55.2%   |
| 15    | Coarse Guassian | 40.2%   |
| 16    | Linear Discriminant | 39.3%  |
| 17    | Quadratic Discriminant | 25.5%  |
| 18    | Guassian Naive Byes | 26.0%   |
| 19    | Kernel Naive Byes | 39.4%   |
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