A Pressure Map Dataset for Posture and Subject Analytics

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***Abstract*— Monitoring sleep postures can provide critical information when analyzing an individual's sleep quality and in-bed behavior. Furthermore, tracking sleep posture over time can play an important role in preventing pressure ulcers (bedsores) in bed-bound patients who are unable to move and change their position frequently. Pressure sensing mats consist of gridded and flexible force sensors are now commercially available for continuously measuring pressure distribution under body parts in different in-bed postures. In this paper, we report the results of a data collection study conducted in two separate experimental sessions from 13 participants in various sleeping postures using two commercial pressure mats. This resource, released publicly, would benefit future research in the area of sleep behavior/quality and corresponding complications. Moreover, we have employed an algorithm based on deep learning for subject identification in the three common sleeping postures using statistical features extracted from the pressure distribution. Our experiments showed promising results in subject identification and further validated the personal sleeping style of each participant.**

I. Introduction

A. Motivation

Sleep is among the most important pervasive characteristics affecting human well-being. Sleep quality is a proven biometric that plays an eminent role in health status evaluation of patients with mental or physical disorders. The quality of sleep is highly correlated with the severity of many illnesses, such as cardiovascular and chronic obstructive pulmonary diseases [1]. The pattern of in-bed postures during sleep is one of the key indicators of sleep quality and can be beneficial for several medical diagnosis or treatment plans such as ones in sleep apnea [2]. For instance, lateral postures are recommended for reducing sleep disorders for mild to moderate sleep apnea, according to [3].

The conventional system for sleep study using neurophysiological signals, polysomnography (PSG), is extremely constrictive and expensive [4]. Furthermore, many PSGs are performed exclusively in hospital environments requiring patients to stay overnight in hospitals. Therefore, in-home sleep monitoring systems have an unmet demand for investigating sleep conditions in a natural setting such as patient's own home environment. At care facilities, documenting residents with sleep-related problems may be useful for deciding on treatment plans and for relieving the workload of night staff.

Pressure ulcers are another category of complications, which are caused by unrelieved pressure during prolonged sleep in a same posture that result in low blood circulation and tissue necrosis. They are extremely common among half body-paralyzed patients suffering from brain infection and elderlies. According to National Center of Health Statistics, pressure ulcers are reported as high as 10% among nursing home residents [5]. Monitoring and relieving pressure experienced at different postures has therefore become a critical step in reducing pressure ulcer incidences in hospitals and nursing homes. Patients are recommenced to be repositioned in a timely manner, usually every two hours to prevent pressure ulcer which is not often practical due to the shortage of caregivers specially in developed countries. Thus, there is a crucial demand for automatic and continuous patient monitoring systems which provide critical information to nurses regarding patient's posture status during a day.

Commercial pressure sensing mats have recently been available to continuously measure pressure distribution under the body while being in bed. These pressure mats report very valuable data which can be used directly by machine learning algorithms to track in-bed postures and assess the experienced stress by each body parts [6]. Please note that we do not suggest that this technology can replace sleep labs. We rather intend it to be a complementary solution to provide supportive information to the caregivers.

B. Related Works

Recently, there has been an increasing interest in sleep quality evaluation, not only for clinical research and for treating sleep disorders, but also in the fields related to the healthcare and health promotion [7]. As a key metric for sleep quality indication, sleep posture detection has been widely investigated [8][9]. Posture detection has also received a great deal of attention in the recent works regarding pressure ulcer prevention using advanced monitoring technologies [10].

Most in-bed posture detection techniques are divided into categories depending on the employed technology such as video cameras, microphones, wearable sensors, or pressure mattresses. RGB data were used to study sleep posture patterns in [11]. Beside violating the privacy of the user, a major technical drawback of using visual signals and video cameras are the lighting issues during the data collection. Visual signals are heavily affected by non-uniform artifacts and noise due to the low light level during nights. Wearable sensors including accelerometers and gyroscopes were used to monitor sleep patterns in [12]. Another technique utilized Electrocardiogram (ECG) measurements to estimate body postures [13]. However, these techniques suffer from being

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obtrusive, since sensors attached to the body or clothing can be uncomfortable or burdensome to the users.

C. Main Contribution

In this paper, we collected in-bed posture pressure data from multiple adult participants using two different types of pressure sensing mats. To the best of our knowledge, our dataset, *PmatData* is the first publicly-available dataset of pressure sensor data which includes various sleeping postures. *PmatData* contains pressure data from two separate experiments. These two experiments are: Experiment I: Pressure data from 13 participants in 8 standard postures and 9 additional states; Experiment II: pressure data from 8 participants in 29 different states of 3 standard postures. Furthermore, Experiment II was collected separately for both regular and air-alternating pressure mattresses. Additionally, we performed subject identification for the three standard postures: supine, right side, and left side. We first extracted 18 statistical features from the collected data in Experiment I and further applied deep learning classifier to identify different individuals. Subject identification using bed posture data has never been performed before. This work is the first attempt to identify individuals based on the data collected from the pressure mats.

II. Data Collection Setup

A. Participants

Our dataset includes bed posture data of 13 participants. A diverse set of participants were chosen as the control to make the dataset reliable for other researchers. All participants were healthy individuals with no history of sleeping disorders or pressure ulcers. The age, weight and height of all participants are given in Table I. Individuals 1-8 participated in both experiments while individuals 9-13 only participated in Experiment I. The data was collected under IRB approval at the University of Texas at Dallas. Informed consents were signed by all participants prior to the data collection and they agreed on the anonymous publication of their data for future research.

B. Apparatus and Materials

Most pressure mattresses available currently in the market provide a 2-dimensional array of sensors which includes a few thousand force sensors. We used the Force Sensitive Application (FSA) pressure mapping mattresses in our experiment. The pressure mat is light, thin, and flexible and covers the entire queen size regular mattress. The electronic interface samples the data every 0.6 second. In Experiment I, the pressure mat has 2048 sensor points with a scan rate of 3072 sensors/second. These sensors are uniformly distributed across a $32'' \times 64''$ mat with each sensor being almost 1 inch apart. In Experiment II, two pressure mats are used, regular mattress and air alternating mattress with sensors uniformly distributed across $27'' \times 64''$ mat with each sensor being almost 1 inch apart. Air-alternating mattress alternate inflation and deflation of air cells (bladders) leading to a change in pressure points. In both experiments, the pressure mats have a sampling frequency of 1.7 Hz and can measure the pressure between 0 to 100 mmHg. The pressure systems used for monitoring are described in detail in the patent [14].

C. Data Collection Procedure

Researchers in [15], investigated the most common postures during sleep of one thousand individuals. The left and right fetus postures i.e. with legs bent, are the most common posture found in almost 40% of the individuals. Additionally, side lying postures with straight legs account for the second most common posture in 28% of individuals. Finally, supine is the third most common posture in 7% of participants. Therefore, we collected data from these postures in our experiments.

1) Experiment I: In experiment I, 8 standard postures were collected for all subjects. The individual maintained a comfortable sleeping position in all postures during the period of data collection. All postures also included a standard non-sensor queen size pillow for the head. The detailed procedure of data collection can be found along with the dataset.

2) Experiment II: In Experiment II, we separately collected data using regular mattress and air-alternating mattress. The postures collected in this experiment included the same ones as Experiment I, however, we collected additional postures. The detailed procedure of data collection can be found along with the dataset. Finally, all these trials are again conducted using an air-alternating mattress in a similar procedure to obtain new data from each individual. Alteration constantly change pressure points and promote circulation in the individual. Therefore, alteration is set at a constant level for all subjects.

D. Dataset Description

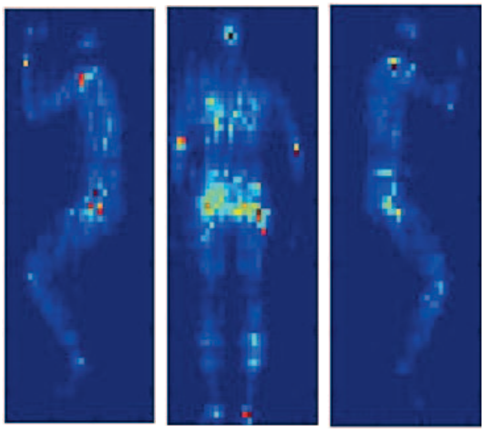
The data is publicly available to download at http://www.utdallas.edu/∼nourani/Bioinformatics /Pressure_Mat_Data.

1) Experiment I: Each posture collected from a participant has a tab delimited .txt file associated with it. The text file of a given posture can be illustrated as a 2D matrix. Matrix $P(t)$ indicates one frame of the body pressure map at sample time t:

$$P(t) = \begin{bmatrix} p_{0,0} & p_{0,1} & \cdots & p_{0,W-1} \\ \vdots & \vdots & \cdots & \vdots \\ p_{H-1,0} & p_{H-1,1} & \cdots & p_{H-1,W-1} \end{bmatrix} \quad (1)$$

where $p_{i,j}$ is the pressure value of the sensor located at (i, j) at sample t, in which $0 \leq i < H$ and $0 \leq j < W$. In this experiment, $H = 64$ and $W = 32$. Fig. 1 shows typical color-coded images from the pressure data of one participant in right, left and supine postures. These color-coded can be made by generating heatmap in MATLAB.

2) Experiment II: Similar to the previous experiment, in Experiment II, each collected posture of an individual has two associated tab delimited text files. The text files are labeled if they are collected using regular mattress or using alternated mattress. The associated matrix $P(t)$ indicates



(a) (b) (c)

Fig. 1: Common bed postures: (a) Right, (b) Supine, and (c) Left.

one frame of the body pressure map using regular or air-alternating mattress as shown in Equation 1. In our system for Experiment II, $H = 64$ and $W = 27$.

E. Technical Validation and Potential Use

Here, we summarize the technical quality and potential usages of the two reported datasets. To validate the accuracy of pressure values exerted, we performed calibration of the sensors after each individual's experiment. The inclusion of wedges in our experimental scenarios allows us to gather data for elevated side postures. This may be suitable for research in other areas such as monitoring sleep apnea and sinus congestion. These datasets have previously been used in [7], [10], [16], [17], and [18] for posture classification and limb identification. To the best of our knowledge, this is the first publicly available data that leverage the use of different postures and mattresses.

III. Subject Identification

A. Feature Extraction

We performed identification of individuals in the three standard postures (i) Supine, (ii) Right side, and (iii) Left side. High classification results on identifying individual participant further validated our dataset and showed each individual has its own personal sleeping pattern. Our dataset contains multiple frames (records) of a posture. For each of these frames, we extracted the pressure sensors which have a non-zero value. This essentially extracts the pressure sensor values associated with each posture. Then, we extracted the following 18 statistical features from the pressure distribution per frame/posture for each participant:
(a) Mean and standard deviation of sensor values of the frame.
(b) Nine quantiles in probability [0.1, 0.9] at 0.1 intervals starting at probability 0.1 of a normal pressure distribution.
(c) Minimum and maximum sensor values of the frame.
(d) Fisher-Pearson coefficient of skewness of the frame, which we formulated as:

$$g_1 = \frac{\sum_{k=1}^{K}(p_k(j) - \overline{P}(j))^3/n}{S(j)^3} \tag{2}$$

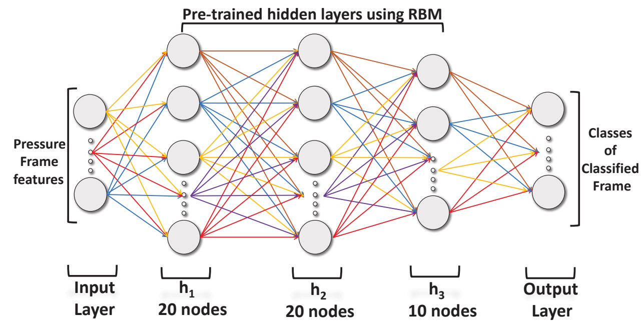


Fig. 2: Final deep belief network for subject identification

where $p_1(j), p_2(j), ..., p_K(j)$ represent the non-zero pressure points of the frame j, $\overline{P}(j)$ and $S(j)$ are the mean and the standard deviation, and K is the number of non-zero points.
(e) kurtosis of the sensor values of the frame.
(f) Discrete values of first, second and third quartiles of the sensor values of the frame.

B. Classification

We used the deep learning approach for subject identification in the three standard postures [19]. We trained our proposed models separately for each posture. However, deep learning models are prone to overfitting, which occurs when the number of training samples is not enough to build a complex model with large number of parameters. We addressed this issue by performing a grid search method to extract the optimal size and number of hidden layers [20]. Our proposed deep learning model consists of 20, 20 and 10 nodes in one input layer, three hidden layers and one output layer, respectively as shown in Fig. 2. We further, incorporated Restricted Boltzmann Machines (RBM) to pre-train the model and find proper initial weights for training deep belief networks [21].

IV. Classification Results

We performed a 10-fold cross validation scheme to test the accuracy of our algorithm. We normalized the values in the confusion matrix from 0 to 100. The confusion matrix for each posture, i.e. (i) supine, (ii) right side, and (iii) left side are presented in Table I. We also reported the accuracy of each posture which is the percentage of correctly classified instances to the total number of instances. According to the Table I, the deep learning is efficiently able to classify subjects indicating that each subject has a personalized sleeping pattern in each posture. Our deep learning model is most accurate in subject identification for the supine posture. As reported in literature, left side, right side and supine are among the most common postures in sleep patterns therefore our approach is efficient to apply to large number of individuals. Most of the misclassifications may have occurred to less training data of individuals. We intend to solve this issue in future works by collecting more data and improving the accuracy of our model.

TABLE I: Subject Identification Accuracy (in %) and Participants' Details for 13 subjects

Posture	Predicted/Actual	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13
Supine	Recall	100	90	90	88.8	80	45.4	90	100	90	90	90	80	81.8
	Specificity	100	100	98.3	99.1	99.1	97.6	96.0	96.7	100	99.1	99.1	99.1	100
	Precision	100	100	81.8	88.8	88.8	62.5	64.2	71.4	100	90	80	88.8	100
	Accuracy						85.5							
Right Side	Recall	70	60	80	70	90	90	70	90	100	100	70	60	90
	Specificity	100	98.4	98.3	97.6	95.2	97.5	99.1	100	97.5	98.3	97.6	100	100
	Precision	100	75	72.7	70	60	75	87.5	100	76.9	8.3	70	100	100
	Accuracy						80.4							
Left Side	Recall	33.3	70	100	100	90	81.8	70	100	100	90	80	80	70
	Specificity	100	96.0	96.7	97.5	99.1	98.3	97.5	99.1	98.3	99.1	98.3	98.3	100
	Precision	100	58.3	71.4	76.9	90	75	87.5	90.9	83.3	90	80	80	100
	Accuracy						82.3							
Participants' Details	Age	19	23	23	24	24	26	27	27	30	30	30	33	34
	Height (cm)	175	183	183	177	172	169	179	186	174	174	176	170	174
	Weight (kg)	87	85	100	70	66	83	96	63	74	79	91	78	74

V. Conclusion and Future Works

Assessment of in-bed postures can be considered of high importance in evaluation of sleep quality and bed-bound patient's health status. Our dataset is one of the first available resource from different postures using pressure mats. This dataset is very beneficial to researchers in the fields such as pressure ulcer prevention, sleep quality assessment, and posture classification. Our analysis further showed that subject identification is efficient in our dataset. This validates that individuals have a personalized sleep pattern and proves that we have extracted discriminative features. Future works include collecting experimental data from a larger group of individuals. We also intend to collect raw sleep data from patients as well as healthy individuals for prolonged periods. Our future works also include collection of pressure mat data for transitional states i.e. when an individuals moves between the standard postures.

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