Recognition of Sleep Patterns Using a Bed Pressure Mat

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ABSTRACT

The monitoring of sleep patterns is of major importance for various reason such as, the detection and treatment of sleep disorders, the assessment of the effect of different medical conditions or medications on the sleep quality and the assessment of mortality risks associated with sleeping patterns in adults and children. Sleep monitoring by itself is a difficult problem due to both privacy and technical considerations. The proposed system uses a bed pressure mat to assess and report sleep patterns. To evaluate our system we used real data collected in Heracleia Lab's assistive living apartment. Our method is non-invasive, as it does not disrupt the user's usual sleeping behavior and it can be used both at the clinic and at home with minimal cost.

Categories and Subject Descriptors

I.5.1 [**PATTERN RECOGNITION**]: Statistical; I.2.10 [**Vision and Scene Understanding**]: Motion

General Terms

Algorithms, Human Factors, Experimentation

Keywords

Sleep Disorders, Sleep Patterns, Machine Learning, Motion Recognition

1. INTRODUCTION

According to the American Academy of Sleep Medicine, there are 81 official sleep disorders, presented in [10]. 70 million people in the USA have a sleep disorder, the vast majority of which remain undiagnosed and untreated. It is estimated that sleep related problems incur $15.9 billion to national health care budget. There is then great need for automatic non-intrusive methods for sleep disorder recognition, that patients can use in their homes. This would not only help decrease health care costs but also increase the number of diagnosed patients.

Another reason why sleep disorder detection is important is the fact that it is related to other potentially more serious medical conditions. According to [5], results of their study involving 1506 participants (out of which 83% reported some medical condition) show that sleep disorders are related to comorbidities rather than age. This is most likely because major comorbidities such as stroke, heart disease, osteoporosis or arthritis impact the patients' quality of sleep. Detection of sleep disorders could therefore be an indication of another important disorder.

[14] studied 917 patients from a wide range of ages and suggest that patients with chronic sleep disorders are more likely to have depression and in fact about 1 in 4 patients who went to a sleep disorder clinic admitted to be experiencing depression, although only 3.5% were found with moderate to severe depression.

We propose a minimally invasive system that is able to analyze and recognize sleep patterns which can be further utilized to detect various types of sleep disorders. Our system uses a bed pressure mat (product of Vista Medical Ltd[1]) where the patient sleeps and data are automatically recorded overnight. The data are then analyzed using Supervised Machine Learning techniques and the system classifies the sleep patterns of the user in one or more predefined categories. In this work we experimented with data collected from 3 individuals.The different patterns included periods of normal sleep and periods of abnormal sleep such as restlessness, and frequent changes of body position. Preliminary results show that our system is able to successfully recognize sleep patterns and classify them among a predefined set of categories.

The remainder of this article is organized as follows. Section 2 presents related previous work in sleep pattern and sleep disorder detection. Section 3 elaborates on our methodology and experimental results in sleep pattern detection. Finally, Section 4 gives the conclusions of our findings.

2. RELATED WORK

Related research has focused on detecting various parameters of sleep for humans and animals as well as sleep quality and body posture recognition. More specifically, studies on rodents focus mainly on detecting if the animal is asleep or awake using piezoelectric films, used as a filtering stage for traditional classifiers using Electroengephalograms (EEG)

[1]http://www.pressuremapping.com/

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and Electromyograms (EMG) [4]. The authors use EEG signals, preprocessed using Fast Fourier Transform (FFT), Principal Components Analysis (PCA) for feature selection and classified using the k-Nearest Neighbour (k-NN) algorithm. [6] also uses EEG and other signals and Markov modeling techniques to classify normal and abnormal human sleeping patterns. These types of signals require traditional Digital Signal Processing techniques such as Discrete Fourier Transform (DFT) and PCA for extracting meaningful features and k-NN or Artificial Neural Networks for the recognition step. Nevertheless, these methods require sensors or cables attached to the skin of the subject which is not acceptable for assistive pervasive applications. Other researchers use additional types of data, such as oxymetry information to detect respiratory abnormalities [8]. The authors evaluate classification results using spectral and nonlinear analysis for feature extraction and Quadratic Discriminant Analysis (QDA), Linear Discriminant Analysis (LDA), k-NN and Linear Regression (LR) for classification. In [7] the authors try to assess sleep quality using near-infrared video only. The authors apply a homomorphic filtering technique to tackle the problem of over exposure in the center, common in near-infrared cameras. The authors also learn a threshold to differentiate noise from actual motion, since this type of cameras have ver low signal to noise (SNR) ratio. They then use the Motion History Image (MHI) technique that provides direction of movement to identify motion.

Pressure has also been used to infer if the subject is asleep or awake by detecting movements and respiration of rodents. There exists one previous approach to our knowledge that recognizes sleeping posture of humans using pressure sensors. More specifically 32 pressure sensors where used to record the pressure pattern of the subject at a particular pose and Naive Bayes as well as Random Forests where used for classification and compared to each other [9]. In [13] the authors use a pressure mat to identify sleeping postures of babies possibly assisting prevention of Sudden Infant Death Syndrome. The authors collected the data from a one year old baby freely moving on the pressure mat and after a feature selection stage they classified each posture using majority vote of k-NN, SVM, linear and quadratic classifiers and then applied a sliding window algorithm to eliminate possible misclassifications.

3. RECOGNIZING SLEEP PATTERNS

3.1 Data collected from FSA bed pressure mat

The FSA bed mat system produced by *Vista Medical Ltd* provides a $1920mm \times 762mm$ sensing area which contains an array of 32×32 pressure sensors. Each of the sensors can capture a measurement in the range 0 to 100 mmHg (1.93 PSI) with a scan frequency of up to 5 Hz. The measurements can be recorded over a period of time and can be exported as a set of time stamped vectors containing the values of each of the 1024 pressure sensors for each time stamp. To make visualization easier we can consider each of these vectors as a frame of a video. Each of the sensors can be considered as pixel of a gray-scale image with an intensity ranging from 1 to 100. Thus each frame can be considered as a 32 by 32 pixel image. Figure 1 illustrates a visualization example of the pressure values captured in one frame. The color coding is just a convention to facilitate visualization. For experimentation purposes we collected data from 3 different individuals. Each subject lied on the mat for about 10 minutes ($\approx$ 1800 collected frames, with a frame rate of 3 Hz), simulating different sleep patterns.

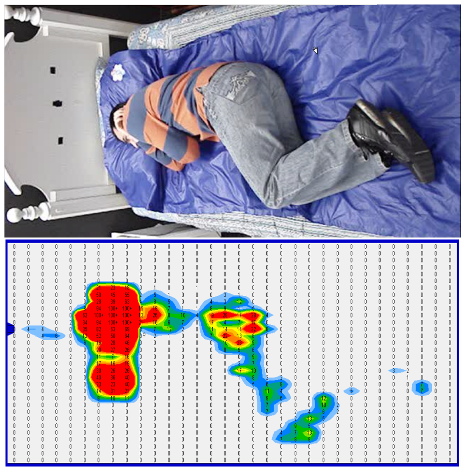

Figure 1: *An example of a subject lying on his side on the pressure mat (top) and the measurement values obtained (bottom).*

3.2 Recognition Classes

The sequences of pressure vector frames obtained by the bed mat can be analyzed in order to extract useful information about the subject's sleep patterns while lying on the mat. In this work, we were interested in recognizing different body postures and different types of motion. This information can be later used in a higher level to automatically detect sleep disorders or can be analyzed by experts to assess the effects of certain diseases or medications in the quality of sleep.

In particular we recognize (1) if the subject is moving or not at each time point, (2) what is their body posture on the bed – (i) lying on their back, (ii) left side or (iii) right side – and (3) the type of motion if they are moving. The motion types that we recognize are (a) turning, i.e. changing side, or (b) just moving some part of their body without changing side.

Since our methodology for recognition of sleep patterns relies on supervised machine learning techniques, manual annotation of the data was required for training and testing purposes. To facilitate the annotation process, each subject was video recorded while using the pressure mad. The video was then synchronized with the time stamped pressure data and each frame of the pressure dataset was labeled as belonging to one or more of the above classes.

3.3 Motion Detection

As a first step we needed to recognize when the subject was moving or not, while lying on the bed pressure mat. This can be achieved by calculating the sum of absolute differences of the values of each of the 1024 pressure sensors between consecutive frames represented as vectors. Assuming a frame vector $X_k = \{x_1, x_2, \ldots, x_n\}$, where $n = 1 \ldots 1024$, at each time point k, this sum S can be can be calculated

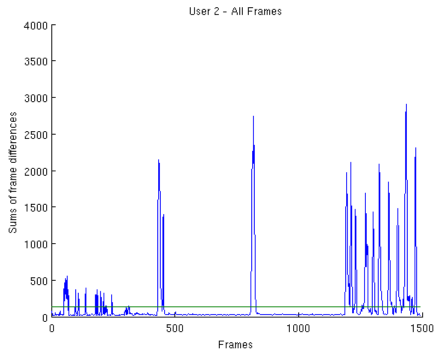

Figure 2: *Detection of motion using the sum of absolute frame differences (S) and a threshold $T = 130$.*

as follows:

$$S = \sum_{i=1}^{n} |x_{k+1,i} - x_{k,i}| \quad (1)$$

It turns out that motion can be easily detected by specifying a threshold T on the value of S. If S becomes greater than T, the subject is moving. The optimal value of T can be calculated from the training dataset and it is almost constant among subjects of similar weights. Figure 2 shows a graph of the values of S over a period of about 1500 frames obtained from one of the subjects. The green horizontal line defines the threshold. In our experiments we found that the optimal threshold value was $T = 130$. This method achieved an average motion detection accuracy of **96.83%** on the data collected from 3 different subjects, with a sensitivity of 92.51% and a specificity of 97.96%. In fact, almost all the misclassified frames belong either at the beginning or at the and of movement of the subject where the levels of motion are very low. This means that when motion occurs it is very unlikely that it will not be detected at all even if some frames of the motion might not be detected.

The above step allows us to segment the data into sequences of frames containing no motion (static frames) and sequences of frames containing motion (motion frames). Each of these sequences can be later classified to one of the body posture classes or one of the motion classes.

3.4 Recognition of body postures

To recognize a body posture in our case means to classify a sequence of frames into one of the predefined body posture classes: (i) lying on the back, (ii) lying on left side or (iii) lying on right side.

In order to perform classification we created a composite feature vector which included as features the 1024 sensor values and the values of the Central Image Moments calculated for each frame. An image moment is a certain particular weighted average (moment) of the image pixels' intensities. For a digital grayscale image with pixel intensities $I(x, y)$, the raw image moments M_{ij} are calculated by

$$M_{ij} = \sum_{x} \sum_{y} x^i y^j I(x, y) \quad (2)$$

The central moments can be calculated using the following equation:

$$\mu_{pq} = \sum_{x} \sum_{y} (x - \bar{x})^p (y - \bar{y})^q f(x, y) \quad (3)$$

where $\bar{x} = \frac{M_{10}}{M_{00}}$ and $\bar{y} = \frac{M_{01}}{M_{00}}$ are the components of the centroid. Central moments are translational invariant.

To remove redundant features and reduce noise before classification we performed a Principal Components Analysis (PCA) [3] transformation on the data. We found that the maximum classification accuracy was achieved when using the first 8 principal components of the transformed data as features for classification.

For the classification of the sequences of static frames into one of the 3 categories we used Hidden Markov Model (HMM). A HMM is a statistical model of a system having hidden states and operating under the Markovian assumption. HMMs have been proven to model effectively temporal sequences as well as other forms of sequential data. The models are trained using the Baum-Welch algorithm that calculates their parameters. As for the recognition step, it is done using the Viterbi algorithm [12].

To evaluate the classification accuracy of our system we performed 10-Fold Cross Validation on the data. Moreover, to increase the reliability of our findings we repeated the cross validation process 10 times and we calculated the average classification accuracy. The accuracy of classifying the sequences of static frames that we got using the above process was **90.4%**.

3.5 Recognition of motion types

Another goal of this work is to recognize and classify motion types. In addition to detecting if the subject is moving or not at each time point, it is of major importance to recognize the type of motion itself, because specific types of motion could be linked to specific diseases or disorders. For example, often movement of the lower limbs could be an indication of restless leg syndrome [10, 11]. In this work we attempt to recognize 2 types of motion: (a) turning, i.e. changing sleeping side, and (b) just moving some part of their body without changing side.

To classify the motion types we experimented with 2 different methods. The fist one involves the same techniques as in the classification of body postures, i.e. Image Moments, PCA, and HMMs. This method produced a classification accuracy of **86.51%**. The reduced accuracy compared to the accuracy obtained for the body posture classification can be attributed to the fact that there is a higher heterogeneity in the motion sequence samples compared to the static sequence samples.

However, we noticed that the shape of the curves created by the sums of absolute differences between consecutive frames (see Figure 2) in the case of turning was different than the one created in the case of minor movements. This gave us the incentive to experiment with a second method for motion detection, which is suitable for matching time series forming some pattern. This method is called Dynamic Time Warping (DTW) [1]. DTW is an algorithm for measuring similarity between two sequences which may vary in time or speed. In our case this attribute is very useful since the pattern of motion, of 2 different turnings for example, could be very similar but the time duration or the speed in which they are performed can significantly vary. DTW measures the similarity of two sequences by calculating the minimum

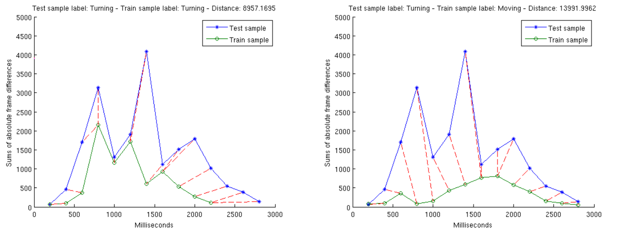

Figure 3: *Example of a two matching (left) and two non-matching (right) sequences of motion using DTW.*

Task	Methods	Accuracy
Motion Detection	Frame Diffs+Threshold	96.83%
Posture Recognition	Moments+PCA+HMM	90.40%
Motion Recognition	Moments+PCA+HMM	86.51%
Motion Recognition	KNN+DTW	90.81%

Table 1: Summary of classification results.

distance that can be obtained when trying to match each of the frames of the first sequence with one of the frames of the second sequence. Note that in order to accommodate speed differences, DTW can match one frame of the first sequence to multiple frames of the second sequence and vice versa.

To better understand the notion of DTW, the reader can refer to Figure 3. The first graph (left) shows the case of two motion sequences of the same type (turning). As one can see, although the two motions follow similar patterns, there is a difference in their time duration. The second graph (right) shows two sequences of different motion types. Although their time duration is the same their motion patterns are very different and so their overall DTW distance greater the previous case.

To perform classification using DTW, one can just find the training sequence that has the smallest distance from the testing sequence and use its label as the predicted label for the testing sequence. This process is basically a K-Nearest Neighbor (KNN) classification [2] which uses DTW to measure similarity between samples. In the above scenario we used $K = 1$, but we could similarly use a $K > 1$. In fact in our experiments we found that the value of K that produced the best accuracy was 10. Our 10-NN classifier using DTW to measure similarity produced an average 10-Fold Cross Validation accuracy of **90.81**% in recognizing motion.

4. CONCLUSION AND FUTURE WORK

In this paper we presented our work on sleep pattern recognition using a bed pressure mat and applying a combination a statistical and machine learning methods. Our preliminary experimental results on real user datasets show that the task of recognizing sleep patterns can be successfully achieved by considering the recognition problem as an instance of pattern classification. Although the available dataset was relatively small, the classification accuracy results (summarized in Table 1) are promising and show that the proposed tools and methods could be used in the future for the detection of sleep disorders and other related diseases affecting sleep quality. To this end, further experimentation with bigger datasets, extended recognition categories and improved methodology would be of high interest.

5. ACKNOWLEDGEMENTS

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