Monitoring Breathing Activity and Sleep Patterns Using Multimodal Non-invasive Technologies

Michalis Papakostas
University of Texas, Arlington
Department of Computer Science
michalis.papakostas@mavs.uta.edu

James Staud
University of Texas, Arlington
Department of Computer Science
james.staud@mavs.uta.edu

Fillia Makedon
University of Texas, Arlington
Department of Computer Science
makedon@uta.edu

Vangelis Metsis
Texas State University
Department of Computer Science
vmetsis@txstate.edu

ABSTRACT

The monitoring of sleeping behavioral patterns is of major importance for various reasons 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 combination of non-invasive sensors to assess and report sleep patterns and breathing activity: a contact-based pressure mattress and a non-contact 2D image acquisition device.To evaluate our system, we used real data collected in Heracleia Lab's assistive living apartment. Our system uses Machine Learning and Computer Vision techniques to automatically analyze the collected data, recognize sleep patterns and track the breathing behavior. It 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. Going one step beyond, we developed a mobile application for visualizing the analyzed data and monitor the patient's sleep status remotely.

Categories and Subject Descriptors

J.3 [**Life and medical sciences**]: Health,Medical information systems; H.1.2 [**User/Machine Systems**]: Metrics—*Human information processing*

General Terms

Human Factors, Measurement.

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Keywords

Machine Learning,Sleep Disorders,Health-care Information Retrieval, Sleep Monitoring, Breath Monitoring, Mobile Applications

1. INTRODUCTION

A sleep disorder is a medical disorder of the sleep patterns that, if left untreated, can lead to sleep deprivation. According to the American Academy of Sleep Medicine, there are 81 official sleep disorders, presented in [5]. Seventy 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 sleep deprivation can lead to traffic accidents, work injuries, increased risk of heart disease, heart attack, high blood pressure, stroke, diabetes, and death. Sleep disorders, according to [13] can also cause mental disorders like depression.

In [12], it is mentioned that especially in older adults, there are three sleep disorders frequently seen: sleep disordered breathing (SDB), restless legs syndrome (RLS)/ periodic limb movements in sleep (PLMS), and REM sleep behavior disorder (RBD). Adults with SDB may experience insomnia, nocturnal confusion, and daytime cognitive impairment including difficulty with concentration.

In the past, some methods using Electroencephalograms (EEG), Electromyograms (EMG) or wearable respiratory sensors have been proposed for sleep disorder monitoring (e.g., [2, 6, 10]). However, these methods are very inconvenient for the patients due to the cumbersome wiring that is required for the bio-signal acquisition. On the contrary to those methods, here, we propose a non-invasive system that is able to analyze and recognize breath and sleep patterns which can be further utilized to detect various types of sleep disorders such as RLS or PLMS. We base our initial approach on the work proposed in [9, 8] and we extend our experimentation by focusing on detecting and analyzing the breathing activity during sleep. Finally, we try to bring the problem on step closer to the real world and out of the lab environment by proposing a mobile application for remote sleep monitoring.

2. EXPERIMENTAL ENVIRONMENT

For applying our experiments we used the equipment of the Smart-Home Apartment, provided by the Human-Centered-Computing-Laboratory Heracleia. We used two different types of sensors, a mattress that measures pressure and a regular web-cam.

The FSA bed mat system produced by Vista Medical Ltd provides a 1920mmx762mm sensing area which contains an array of 64x27 pressure sensors. Each of the sensors can capture a measurement in the range 0 to 100 mmHg with a scan frequency of up to 5 Hz. The measurements can be recorded and manually annotated over a period of time and can be exported as a set of time stamped vectors containing the values of each of the 1728 pressure sensors for each time stamp.

The web-cam resolution was 1080x720 and it was place on the side of the bed and a few inches above its surface.

3. SLEEPING POSTURE RECOGNITION

We implemented the sleeping posture recognition using the the data stream provided by the pressure mat.

The output of the pressure mat is a vector with 1728 features. Each feature represents the output value of each pressure sensor. Thus each feature has a value between 0 and 100. Since the nature of these row data (range of values) are similar to a gray-scale image we try to handle this problem as an image-processing problem. Each of the sensors can be considered as a pixel of a gray-scale image with an intensity ranging from 1 to 100. Thus each frame can be considered as a 64 x 27 pixel image.

For experimentation purposes we collected data from 5 different individuals. All individuals were of average weight and height. Each subject lied on the mat for about 5 minutes , simulating different sleep patterns. In total five different sleeping patterns were simulated. In particular we recognized if subjects are (i) lying on their back, (ii) on their stomach, (iii) left side or (iv) right side and (v) if they were just sitting on the bed. In Figure-1 we display a visualization representation of the pressure values captured in one data-frame for each different posture.

To perform classification we separated the data into 5 equal subsets, where each subset was related to a specific subject. Each subset contained 100 feature vectors (pressure mat scans) to represent each class (5 classes in total, each related to a different posture). Thus each subset had 500 training samples, which represented all the classes. We used 4 out of the 5 subsets to train our model (thus 400 samples per class and 400*5=2000 training samples in total) and the 5th subset (500 test samples in total - 100 samples from each class) was used to evaluate our system. For a more efficient evaluation we performed 5-fold cross validation.

We used PCA to reduce the data dimensions from 1728 to 20 features and we tested two classification approaches using KNN-1 and 1vsAll SVM using a linear kernel. Table-1 illustrates the classification accuracy percentages for each class, while Table-2 displays the average accuracy for each different classifier.

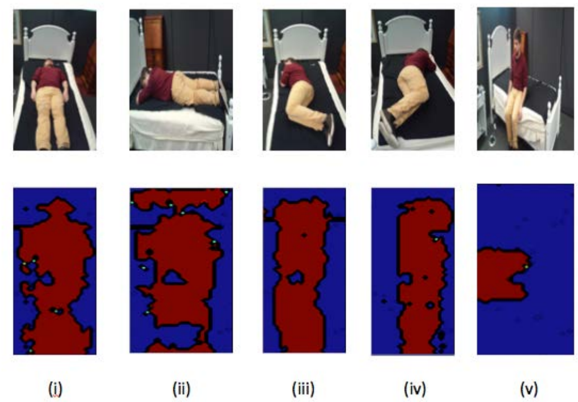

Figure 1: Images on the top display the actual posture while bottom images illustrate the visualization of the output from the pressure mat

	Back	Stomach	Right Side	Left Side	Sitting
SVM	66.4	100	60	80	100
KNN-1	63.2	82.6	60	74.8	80

Table 1: Classification Accuracy per Class (%)

	Average
SVM	81.28
KNN-1	72.12

Table 2: Average Classification Accuracy (%)

The classification results come to validate previous findings [9, 8], which also claim that SVM based classification can lead to more accurate results. However, during the experimentation we realized that efficiency is highly depended on the body proportions of each subject. Moreover as the subject change postures the pressure mat produces inevitably noisy measures, which complicate our problem. Thus, the use of additional sensors as proposed in [9, 1, 7] may lead to higher and more robust accuracy.

4. MONITORING BREATHING PATTERNS

To monitor the breathing patterns during sleep we developed a system, which combines the data taken from a regular web-cam and the output stream of the pressure mattress. We applied standard computer-vision techniques to monitor in real-time the movement of the chest as the subject breaths and a simple offline analysis of the data taken from the pressure mat over-time.

4.1 Monitoring Chest Movement

To monitor the chest movement we developed a motion tracking algorithm using the frame difference technique (*equation 1*).

$$\begin{cases} Diff_i = I_{k+2} - I_k \\ Diff_{i+1} = I_{k+4} - I_{k+2} \end{cases} \tag{1}$$

A web-cam was placed on the left side of bed and few inches

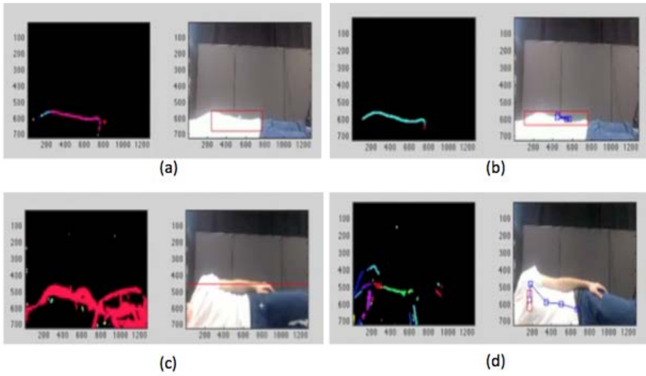

Figure 2: (a) Motion has been detected - system has not lock to a target yet, (b) System locked to the target after detecting movement in 15 sequential frames, (c) Unexpected motion occurred due to change of posture - motion detected but not tracked, (d) System re-locked to the chest area when breathing pattern detected

above its surface. The camera was placed properly to capture only the region of the subject's chest. Using this simple approach we were able to detect quite accurately the motion at the area of the chest while the subject was breathing.

Any other motion except, the movement of the chest, was considered as noise and thus, we did not want to take it into consideration. To prevent our system from getting confused by such kind of noise we applied a hysteresis threshold to cut of any other transient movement (such as a change of posture, an unexpected hand movement etc.)(Figure-2). The camera captures about 15 frames per second, however, for better motion detection, only every second frame is being processed (6 to 7 FPS). Under regular breathing conditions, movement was detected every 0.3 seconds. If motion occurs constantly in 15 sequential processed frames (around 2.5 seconds), in a certain region of the frame, the system locks in this area and the motion tracking begins. Since breathing can be considered as an almost periodic event, the system apparently locks and tracks only the area of the chest where consistent movement occurs. If no motion is detected for a certain amount of time, which was set to 20 processed frames (about 4 seconds) the systems "forgets" the targeted area and unlocks from the target. In such case we have to consider the possibility that our subject had a breathing failure.

4.2 Measuring Motion Level

Additionally to the vision-based breath monitoring we used the pressure mattress device to monitor the levels of motion over time. We hoped that as the subject breathes we could observe greater fluctuations to the output stream of the pressure sensors that lie under the chest. The subjects were asked to lie on their back, remain still and just breath. They were also encouraged to take both regular and deeper breaths. We collected data for 4 minutes.

The pressure pad provides 1 data-frame every 0.25 seconds.Hence, we could collect 4 different measures from each pressure sensor every second. To analyze the output stream and measure the levels of motion over time, we subtracted from each data-frame the average of the 10 previous frames

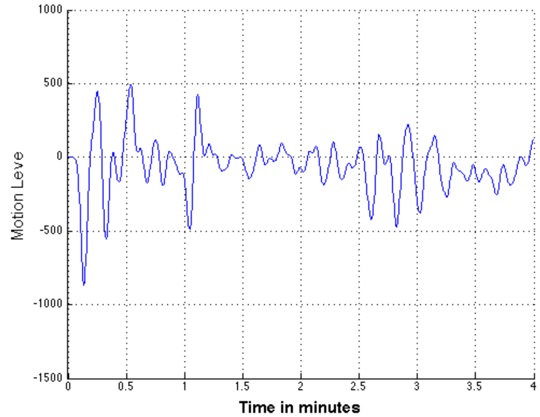

Figure 3: Motion level over time

(*equation 2*). Then for each data-frame we summed all the pressure values. Thus, every data-frame was represented by a single value (*equation 3*). For the 4 minutes of experimentation, we collected in total 803 such values. Each of these values can be considered as an indicator of the pressure applied to the pressure mat at each moment. Before visualizing the data we applied a Gaussian filter to smooth the curve.

$$F'_{i+10} = F_{i+10} - mean\{F_i, F_{i+2}, ...F_{i+9}\} \tag{2}$$

$$F''_i = \sum_{k=1}^{1728} v_k \tag{3}$$

In the graph of Figure-3 we can observe periodic-like peaks of different amplitude, which refer to different amounts of pressure applied to the pressure mat over time. Since the subjects remained motionless it is obvious that these variations on the pressure, indicate the motion caused by the breathing activity. Higher amplitude can be translated as "deep breathing" while low amplitude combined with low frequency can be an indicator for respiratory problems or even breathing inactivity.

4.3 MOBILE APLICATION

In order to relay the information that is collected by the sleep monitoring system, the data must be aggregated and then displayed to the person who is responsible for monitoring the sleep patterns. This task was achieved through a mobile application interface on the Android and iOS operating systems. In the mobile application, the data is represented in multiple ways.

Initially the app was intended to visualize the data using a heat map of the mattress showing pressure in certain areas, however, this was proven to be useless data to the observer in the manner we were visualizing it. Visualizing data in this way is going to be further evaluated using iconographic maps or three dimensional heat maps involving color, depth, and density[3, 11]. Instead of a heat map, the data is represented through two dimensional area charts, line charts, and pie charts in order to give the best perspectives on the sleep information for the quick retrieval and comprehension of the

(i) (ii)

Figure 4: (i) Android Version, (ii) iOS Version

patterns[4] throughout the entire sleep cycle. A donut chart is used to represent the breathing pattern averages for each hour during sleep and then display the largest average in the center to present the problem area automatically.

Alerts proved to be a useful feature for personnel in charge of monitoring any sleep interruptions to prevent injury to the resting patient, therefore, we implemented an alerts feature which would allow the app to display any alerts from the system which catch any interruptions throughout the sleep cycle. The applications interface followed the platform standards for design patterns and user experience flow patterns in order to insure the user would intuitively understand how to operate the application without the need for introductory dialogues.

There are three main fragments inside the application: A dashboard including all of the data visualizations, an alerts page showing all of the alerts sent from the monitoring system, and a settings page to toggle the network data collection. The data is populated dynamically from a middle-ware web server which aggregates the data and then makes it available to the mobile application through a RESTful API. The middle-ware server collects the data from the monitoring application and stores it in a database. The data aggregation is performed on the web server and it includes the following: Taking the breathing patterns and averaging them over an hour, day, and month, averaging the pressure on the mattress, and averaging the pressure averages over an hour, day, and month.

5. CONCLUSIONS AND FUTURE WORK

We proposed an initial approach for a robust, non-invasive multi-modal sleep monitoring system using low cost technology. Our work comes to extend previous findings and techniques [9, 1, 7] in sleep posture recognition by providing an additional functionality for breath monitoring and a user-friendly way for data visualization. Our findings prove that breathing patterns can be monitored and identified and possible respiratory failures can be immediately prevented.

Our next goal is to extend the proposed modules to perform a real-time analysis. At the same time we plan to enrich our sensing environment with supplementary low-cost sensors to identify additional sleeping event such as RLS or PLMS.

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