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MONITORING OF RESPIRATORY CYCLES UTILIZING SENSORS ON SLEEPING MAT

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ABSTRACT

Sleep apnea and other sleeping disorders impair health and quality of life. Polysomnography is the primary method for diagnosis, but involves cost and utilization of medical resources, which limit access for potential patients. The clinical environment and sensors of polysomnography hinder typical sleep patterns in many individuals, thus degrading the analysis. Sensors suitable for at-home monitoring of sleep have recently become available. At-home monitoring of sleep may improve diagnosis due to increased familiarity for sleeping and ability for multiple sleep sessions, as well as lowering the cost. However, more robust algorithms would be needed to partially compensate for the less controlled conditions and sensor systems. A mat with a grid of force sensors has become available. This study was developing a state machine algorithm to analyze the activity at multiple force sensors of a mat while the subject was lying in supine position on the mat and undertaking natural, rhythmic respiration. The algorithm monitored the subset of active sensors to detect potential respiratory cycles. The similarity of the timing of the detected cycles between different sensors was used to determine the overall pattern of respiratory activity for the subject. Reliable detection of timing for respiratory cycles would be useful for detection of sleep apnea events.

INTRODUCTION

Sleep disorders, such as sleep apnea, reduce the quality of sleep and are associated with increased risk of daytime drowsiness, heart conditions, high blood pressure, stroke and cognitive decline [1-3]. The incidence of sleep disorders increases with old age and obesity [4-6].

The primary form of diagnosing sleep disorders is a polysomnography session, in which the subject is connected to multiple monitoring sensors and recording systems, and tries to sleep during the session. Sensors for recording and analysis include electroencephalogram, electro-oculogram, electrocardiogram, electromyogram, nasal airflow sensor and a microphone [7, 8]. The typical pattern of sleep is hindered in some patients due to the combination of being in an unfamiliar clinical environment, being connected with many wired sensors and air flow monitors, and the presence of medical staff. Polysomnography sessions also have high cost that limits accessibility. Many individuals having sleep apnea and other disorders are estimated to remain undiagnosed and untreated, increasing the risk of health impairments and lower quality of life.

Efforts have been made to diagnose for sleep apnea without undergoing a full polysomnography session [8, 9]. These efforts usually attempt to analyze a smaller set of recorded signals or take place in a more natural setting.

Examples include using primarily audio sounds [10], a standard hospital patient monitor [11], and at-home sleep monitoring [12, 13]. These alternative methods show promise but more development is necessary to improve diagnosis.

The rhythmic cycle of respiration has been used to develop state machine algorithms that have been shown to detect inspirations from analysis of several respiratory signals, including diaphragm electromyography [14, 15], central venous pressure [16], intercostal muscle electromyography [12], and human respiratory signals recorded during a sleep study, including air flow, ribcage and abdominal movements [17].

A "smart rubber" mat with a grid of pressure sensors for monitoring pressure points of a human lying on top has become available (Body Pressure Sensors, Sumitomo Riko Company Ltd., Komaki, Aichi, Japan). This study developed a state machine algorithm to analyze the activity at multiple force sensors of this mat while the subject was lying on the mat and undertaking natural, rhythmic respiration. The algorithm was developed to determine which sensor nodes had the most activity, and applied the state machine algorithm to each of those active nodes for the detection of respiration cycles. The timing of the detected respiration cycles of the different nodes was compared toward determining which nodes had the most similar activity.

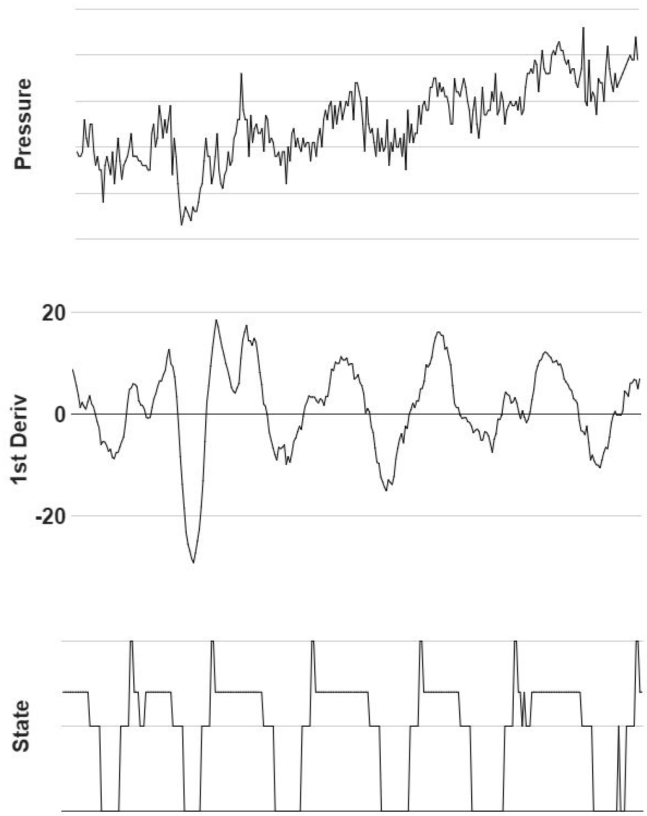
The development of such algorithms would support utility of pressure mats for at-home monitoring of sleep. Reliable detection of timing for respiratory cycles would be useful for detection potential sleep apnea events or other sleeping disorders.

Recording of Signals

The "smart rubber" mat (Sumitomo Riko Company Ltd., Komaki, Japan) was utilized for recording. An adult male subject laid on top of the mat in supine position for the recording session. The layers under the subject were as follows from bottom to top: hard surface, futon mattress, smart rubber mat, cloth sheet, and the subject. The mat was long enough to extend from the head to the waist, and wide enough to extend beyond the shoulders. The mat had a 2 dimensional grid of sensor nodes for pressure, having a total of 1057 sensor nodes. The sampling frequency was 20 Hz and the recording session lasted just over 6 minutes. The subject underwent normal rhythmic breathing while lying still on the mat during the recording session. The recorded data values were stored in a text file for later data analysis.

Signal Processing

A custom LabView program (National Instruments, Austin, TX) was developed to analyze the recorded data. The data was read from the text file and organized in a 2-dimensional matrix of pressure values with each column being one of the 1057 sensor nodes, and the rows being one of the 7215 sequential samples (20 Hz for just over 6 minutes).



Time (s) *for a 15 second period*

Figure 1: Example of signals from one sensor node of the mat. The top trace shows how the pressure values changed over the 15 seconds of the example trace. The middle trace shows the first derivative of the pressure trace calculated using a 1 second moving time window. The bottom trace shows the states of the state machine algorithm that were determined based on the first derivative signal. The highest peak of the state trace indicated when the cycle of respiration was detected by the algorithm. That time of detection was stored in an array for that node.

Not all sensor nodes had contact with the body of the subject. The cycles of respiration generated more movement in certain body locations compared to others. Since the subject was trying to lie still while breathing normally, the nodes with the most activity should be the nodes with the most useful respiratory information. Standard deviation was calculated for all the samples of a node. The higher the value of standard deviation, the more active the node was considered to be. The values of standard deviation were sorted and the most active 5% of the nodes were selected (53 nodes) for further analysis.

A cycle of respiration involves a phase of inspiration followed by a phase of expiration. The first derivative of the pressure values was calculated and used to differentiate these phases. A moving time window of 1 second (20 sample points) was used to fit a linear line, with the slope being saved as the first derivative value for that point. The moving time window had the effect of smoothing out some of the noise variations in the recorded values.

Figure 1 shows an example 15 seconds of these signals. The data points for this trace were from the node with the highest standard deviation, and so was considered to be the most active node. The top trace shows the pressure values. The middle trace shows the first derivative of the top trace calculated using a 1 second moving time window.

State Machine Algorithm

The state machine used for this study was based on the algorithm developed for a prior respiration study [16]. A state machine has the advantage of matching the functional sequence of the respiratory "machine" necessary for exchange of gases, consisting of a phase of inspiration followed by a phase of expiration.

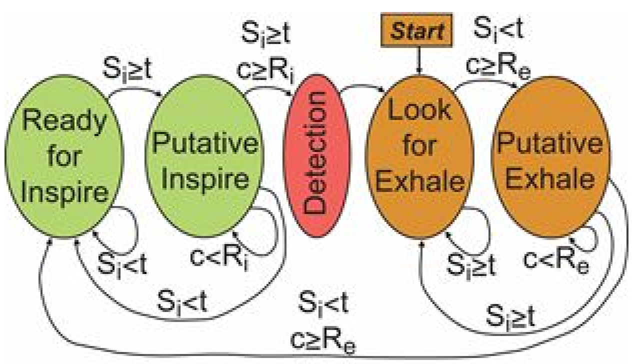


Figure 2: State machine used to characterize the state of the respiratory cycle based on the first derivative (S_i) values. To pass from the Look for Exhale state to the Putative Exhale, the S_i value needed to be below the Threshold value (t). Then to pass to the Ready for Inspire state, the S_i value had to remain below t for R_e samples. Similarly, to pass from the Putative Inspire state to the Detection state, the S_i needed to remain equal or above t for R_i samples. The Detection state would indicate that an inspiration had been detected. The time at this detection would be recorded as the time to mark one cycle of respiration.

The first derivative values for a node (as shown in middle trace of Figure 1) were designated as S_i, and were input to the state machine in sequential order. A diagram of the state machine is shown in Figure 2. The variable t is the threshold and was 0 for this study, differentiating positive and negative first derivative values. The value c was a count of required number of sequential values to be above or below the threshold (t=0) to progress to the next stage. R_i was the number of the sequential count to progress from Putative Inspire state to Detection. R_e was the number to progress from Putative Exhale state to Ready for Inspire state. In this study both the value of R_i and R_e were set for 300 ms, so was 6 sample points. The time when the Detection state was entered was saved as time to indicate the occurrence of one respiratory cycle.

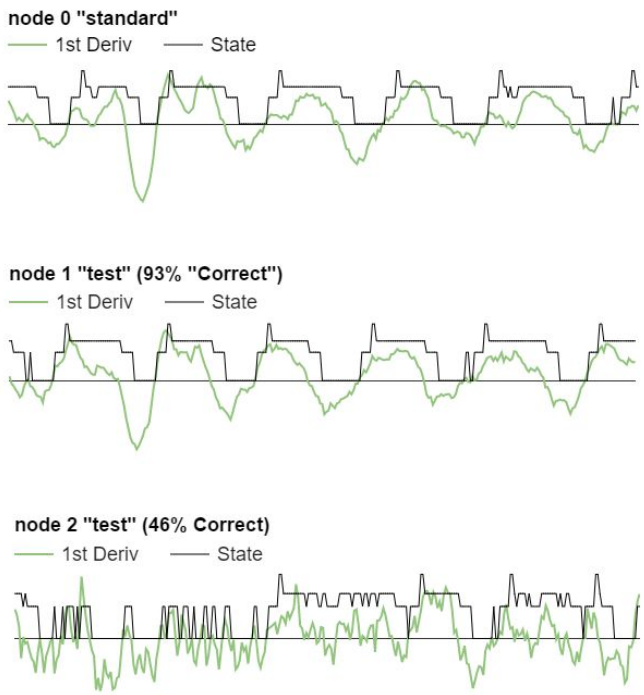
The bottom trace of Figure 1 shows the changes in the state by the progression of the state machine analyzing the S_i values (first derivative, middle trace of Figure 1). The Ready for Inspire state was assigned the lowest value, and the Detection state was assigned the highest value of the trace. Thus, the rising edge of the state trace that reached the highest level indicated the time of detection of one cycle of respiration. This time was saved in an array of detection times for that sensor node.

Characterize Similarity

To characterize how similar the respiration detection timing of one sensor node were to other sensor nodes, a Percent Correct value was calculated for each pair of nodes as follows. One node was considered as the "standard" node and the other node was the "test" node. The timings of the "standard" node were considered the "correct" values. A time window was formed around each detection time of the standard node, with the window defined from a begin time to an end time. The begin time was halfway between this standard time and the prior standard time. The end time was halfway between this standard time and the next standard time. For the "test" node to be "correct" for this "standard" detection time, one and only one "test" node time must have occurred within this window between the begin time and end time. The number of "standard" times having a "correct" match with the "test" node were counted and divided by the number of detection times of the "standard" node, to form the Percent Correct value.

Results

Figure 3 shows an example comparison of node 0 as the "standard" node to two "test" nodes, node 1 and node 2. The traces in Figure 3 show a 15 second example period, but the Percent Correct value was calculated from analysis of the full 6 minute recording. Node 1 had timings that more closely matched the "correct" timings of node 0, and had a higher Percent Correct value of 93%. Node 2 had timings that did not match as well the "correct" timings of node 0, and had a lower Percent Correct value of 46%.



Time (s) *for a 15 second period*

Figure 3: Example traces with node 0 being the "standard" node and nodes 1 and 2 being the "test" nodes. The Percent Correct value of node 1 to node 0 was calculated, as well as node 2 to node 0. The traces show a 15 second example, but all 6 minutes were used for the calculation of Percent Correct. The timings of node 1 more matched the timings of node 0. The timings of node 2 less matched the timings of node 0.

Each of the selected most active nodes were compared to the other nodes. Table 1 shows the Percent Correct values of the 5 most active nodes.

DISCUSSION AND FUTURE DIRECTIONS

The Percent Correct calculations of the developed algorithm do seem to help identify nodes that have similar respiration detected timings to one another. Further analysis would be necessary to identify a subgroup of nodes that show close correlation to one another (relatively high Percent Correct). Such a subgroup of cells may best reflect the overall pattern of respiration for the subject lying on the mat.

More testing will be required to compare the detected respiration timings with the actual respiration behavior. Disturbances to the pattern due to body movement unrelated to respiration would need to be managed, such that the active respiratory subgroup of nodes would dynamically adapt to the current situation.

An algorithm that would detect the timing of respiratory cycles of a subject lying on a sleeping mat would enable an at-home monitoring of sleep that would enhance monitoring and potential detection of sleep disorders while a subject is sleeping in their normal home environment with minimal sensory equipment that would hinder the typical pattern of sleep in some subjects.

Table 1: Percent Correct calculations. The node labeled at top of each column was the "standard" node, compared to all other nodes. The diagonal cells are blank as a node was not compared with itself.

	node 0	node 1	node 2	node 3	node 4
node 0		93%	61%	81%	56%
node 1	93%		55%	73%	57%
node 2	46%	40%		46%	59%
node 3	81%	76%	53%		57%
node 4	44%	34%	57%	46%	

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