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Sleep and Activity Monitoring for Returning Soldier Adjustment Assessment

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Abstract—This paper describes the development of unobtrusive room sensors to discover relationships between sleep quality and the clinical assessments of combat soldiers suffering from post-traumatic stress disorder (PTSD) and mild traumatic brain injury (TBI). We consider the use of a remote room sensor unit composed of a Doppler radar, light, sound and other room environment sensors. We also employ an actigraphy watch. We discuss sensor implementation, radar data analytics and preliminary results using real data from a Warrior Transition Battalion located in Fort Gordon, GA. Two radar analytical approaches are developed and compared against the actigraphy watch estimates – one, emphasizing system knowledge; and the other, clustering on several radar signal features. The radar analytic algorithms are able to estimate sleep periods, signal absence and restlessness in the bed. In our test cases, the radar estimates are shown to agree with the actigraphy watch. PTSD and mild-TBI soldiers do often show signs of sporadic and restless sleep. Ongoing research results are expected to provide further insight.

I. Introduction

This paper describes continued research and development efforts for a government funded health research program conducted at Fort Gordon, GA. The background, system design and physiological laboratory results were published in EMBC in 2011 Proceedings [1]. The current paper focuses on system implementation and data analytics.

The Returning Soldier Adjustment Assessment (RSAA) research seeks to investigate sensor technology that remotely measures sleep and activity in combat soldiers suffering from traumatic brain injury (TBI) and post-traumatic stress disorder (PTSD). The development of reliable in-home monitoring technology and discovery of correlation between sleep and periodic clinical assessment potentially offer advances in military wound care and telemedicine in general.

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TBI and PTSD are increasing concerns for soldiers returning from combat. TBI has become the so-called signature wound of modern, asymmetric warfare. Concussive brain injuries are often severe and survivable due to improved protective combat gear. Even milder, but repetitive, blast injuries may have long term ramifications for pain, individual behavior and memory loss [2]. As of March 1, 2012, the US Army has experienced over 45,000 soldiers wounded in action (WIA) in Middle-Eastern theaters of operation [3].

TBI and PTSD sufferers often experience an inability to fall or remain asleep. Poor sleep can have adverse impacts on cognition, attention, and judgment. Disrupted sleep has also been shown to delay and impair rehabilitation [4]. Research and development of unobtrusive technology for measuring sleep quality is an important step towards understanding the day-to-day impact of TBI and PTSD, and potentially improving treatment.

RSAA study subjects volunteer to participate for thirteen weeks during which unobtrusive sensors infer sleep and activity. Subjects complete several periodic assessments including the Pittsburgh Sleep Quality Index [6] and HIT-6 [7], and receive periodic clinical assessments which are used to explore the relationship between PTSD/TBI and sleep/activity. The research team is composed of scientists from G.E. Global Research, along with clinicians from the Eisenhower Army Medical Center (EAMC) and Georgia Health Sciences University. Subjects are recruited and enrolled from the Warrior Transition Battalion (WTB) at Fort Gordon, GA.

The remainder of this paper is organized as follows. System implementation is discussed in section II and radar sleep estimation in section III. Algorithm performance is evaluated in section IV. Conclusions and future work are covered in section V.

II. System Implementation

A. Sensor Descriptions

Figure 1 Room sensor unit.

Sensors are installed to measure and derive sleep and activity. An in-barracks system of sensors consists of Doppler radar, temperature, humidity, motion, light and sound, and is referred to as the room sensor unit (RSU). Sensors operate at a 40 Hz sampling rate. The RSU is installed on a wall cabinet above the head of the bed in the rooms of participating subjects as shown in Figure 1. An actigraphy wristband is also continuously worn by each subject measuring his or her motion 24x7.

B. Study Data

Twenty-two subjects have enrolled in the study to date. Subjects were recruited from nearly 700 soldiers routinely seen in the EAMC TBI and Behavioral Health clinics. The primary reasons offered for declining to enroll were: transferring to other facilities (45%), returning to active duty (20%), and not interested (15%). Subject data are collected periodically by the onsite research Study Coordinator and recorded to a database for comparison with corresponding clinical assessments. Approximately 60 gigabytes of room sensor data have been collected, representing 1,200 days. In addition, 1,500 days of actigraphy watch data were logged. Approximately 2,500 sleep intervals have been measured, along with over 200 subject assessments.

In this preliminary report, we consider cases from two several subjects. The first two data sets cover 16 hours when the subject is known to be in the room and asleep during the night. The third data covers an entire week. Preliminary data analyses indicate that RSU sensors can reliably measure bedtimes and periods of sleep and rest, when compared with existing methods such as actigraphy. Further subject data and analysis will be required to statistically test and validate each study hypothesis, once the study concludes.

III. Sleep State Estimation

This section describes the analytic approaches used in extracting sleep information from the radar and actigraphy measurements.

A. Radar State Estimation

The Doppler radar measures an individual's in-bed, recumbent motion, ranging from highly restless to the gentle chest and rib motion of respiration and heart pulsation when

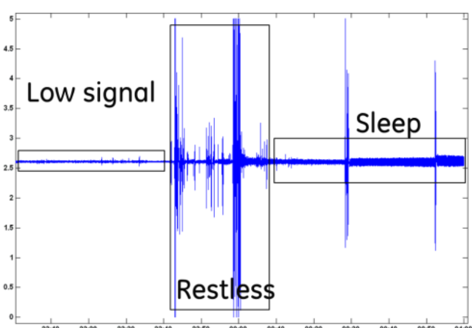


Figure 2 Radar signal.

a person is sleeping. Radar analytics seeks to classify these radar measurements into one of three physical states: #1, lack of motion (low signal); #2, person in bed restless; and #3, person in bed asleep. The radar measurements occur between 0 and 5 Volts. An example of a radar signal is labeled with each state in Figure 2. The lowest energy signals correspond to state #1; the spiky signals with large instantaneous energy changes correspond to state #2. Lastly, the steady sinusoidal signals correspond to state #3, when a subject is asleep and breathing normally. Often in state #3, chest motion can be directly observed in the radar signal, thereby enabling estimation of breathing and heart rates [1], [6], [9] – which can potentially be used for sleep stage research in the future.

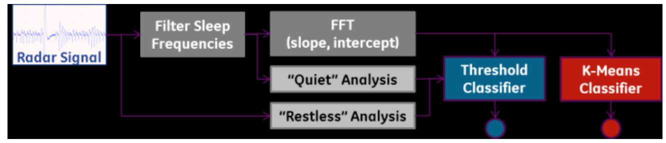


Figure 3 Radar analytics process

As depicted in Figure 3, radar signal processing involves several steps. First, the signal is mean-subtracted and then passed through a 10 Hz low-pass filter. Higher frequencies are unnecessary for estimating breathing and heart rate. The filtered time signal is then sequentially divided into 30-second windows and processed in 1-second sliding intervals. The Fast Fourier Transform (FFT) of each time window is computed to obtain a short-time log-magnitude frequency spectrum of the signal. A first-order linear regression is then fit to this spectrum between the frequencies of 0.1 to 0.5 Hz, corresponding to 6 to 30 breaths per minute. The slope and intercept of the regression line are used as sleep signal features. These features were selected through repeated trial

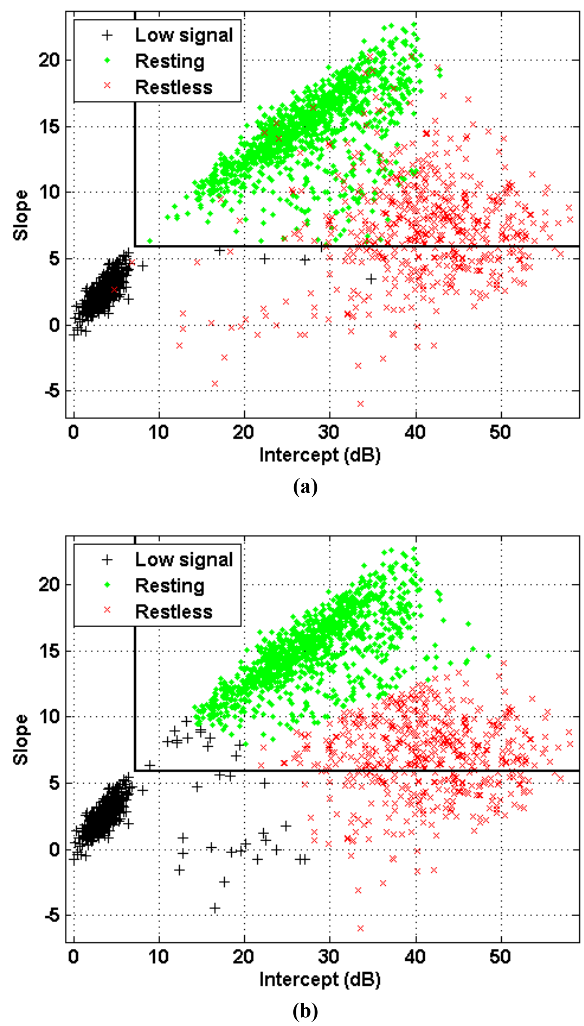


Figure 4 Scatter plot of the two spectral features, slope and intercept, using (a) adaptive thresholding and (b) k-means clustering for Subject #1.

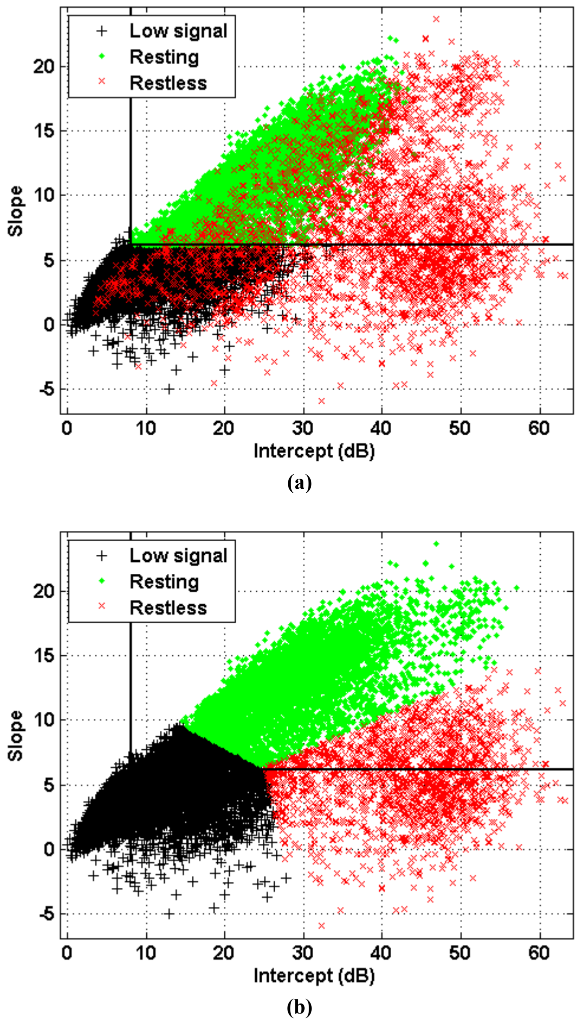


Figure 5 Scatter plot of the two spectral features, slope and intercept, using (a) adaptive thresholding and (b) k-means clustering for Subject #3.

and error. Additional features, such as peak-to-average ratio were tested and evaluated using principal component analysis (PCA) without producing any significant advantages. The slope of the fitted line measures the rate of change between the lower sleep frequency signals and higher non-sleep frequency signals, thus providing a *sleep signal* feature. The intercept captures the average *energy* of the signal. Together, these features enable sleep classification. Scatter plots of these features are shown for two subjects in Figure 4 and Figure 5, with slope plotted on the vertical axis and intercept on the horizontal axis. Plots (a) and (b) differ in approach which is explained next.

1) First Approach: k-Means Clustering

Interestingly, three *natural* clusters emerge when the radar features are plotted in each case, corresponding to the three physical states anticipated and described earlier. The first cluster, with the lowest intercept and slope values, corresponds to low signal, or state #1. The second cluster, with highest intercept values, corresponds to restlessness, or state #2. A final cluster corresponds to sleep/resting, or state #3 signals.

In order to classify the data into these meaningful states, several methods were considered. Ultimately, k-means clustering offered a reasonable unsupervised means of feature classification. This is referred to as the k-means classifier and its results can be seen in Figure 4b and Figure 5b for Subjects #1 and #3, respectively.

2) Second Approach: Adaptive Thresholding

Alternatively, feature thresholds can be developed from the data – which also conform to the three state clusters. These thresholds are plotted as solid lines in Figure 4 and Figure 5 for reference. However, the threshold approach is only specifically shown in plots (a).

In this method, the algorithm quickly searches through the presented data set to find several (arbitrary) intervals with the lowest signal energies. (It is assumed that the room is empty for several hours within each data collection interval.) For instance, the algorithm can search for the quietest 3 hours during a 7-day interval. The distribution of the features obtained during these quietest periods is then used to obtain baseline thresholds for slope and intercept. Three standard deviations are added in our analysis. Once these lines are drawn, the region between quiet (low signal) and sleep (higher slope) can be discovered.

Additionally, it was observed that a third feature, a sampling of the maximum voltage levels, obtained when computing slope and intercept, could be used to improve classification results for both approaches. When a given maximum voltage (within the 30-second analysis windows) is larger than a certain value, say a *restless* threshold, the subject must be in-range, but *causing* too much motion to be asleep. The *restless* threshold might be set to either a fixed, calibrated value or adaptively discovered from the data. In our analysis, we used the average maximum voltage computed from the data set under consideration. Adaptive thresholds are plotted consistently in both Figure 4 and Figure 5.

As a final observation, when the radar is functioning soundly and the subject presents a good profile, as in Figure 4, clusters are well-defined and both methods (k-means and adaptive thresholding) produce similar results. Otherwise, when signals show little separation, (see Figure 5), unsupervised clustering tends to give rather arbitrary decision boundaries. Our work then suggests the alternative, adaptive thresholding method should be selected.

B. Actiwatch State Estimation

The Actiwatch® software analyzes the wearer's daily activity and estimates patterns of activity, rest and sleep [5]. For this study, 30-second epochs were configured. Epochs are classed as either active, rest, or sleep determined by a sliding window algorithm and various (tunable) activity thresholds.

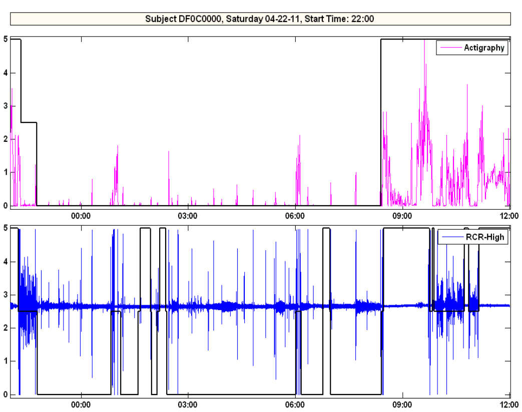
In the current analysis, Actiwatch pattern estimates are used to evaluate corresponding RSU patterns. However, in the future, the RSU and actigraphy patterns will be combined, taking advantage of the strengths and weaknesses of each method. For instance, RSU patterns are only valid when the subject is in the room, whereas the Actiwatch measures activity anywhere – as long as the wristband is worn. In practice, the Actiwatch algorithm generally focuses on identifying a single, well-defined interval of daily sleep, from which to obtain sleep metrics including sleep latency, efficiency, and et cetera. In this sense, actigraphy *ignores* naps. Without any complex reasoning at present, the RSU radar recognizes even small sleep intervals and restlessness throughout the day. This may prove extremely important when evaluating behavioral health including depression.

IV. PERFORMANCE EVALUATION

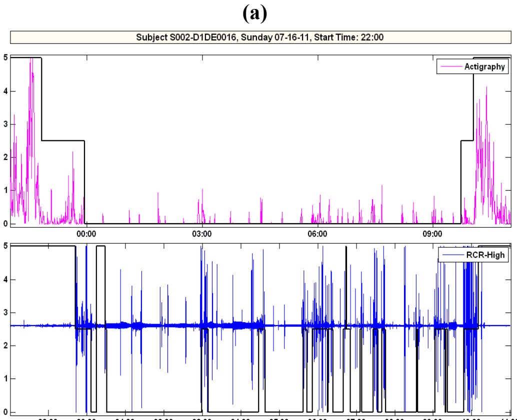
A. Actiwatch versus Radar

In Figure 6, we compare the Actiwatch and the radar results. The plots were normalized between 0 and 5 Volts. The radar state estimates are obtained by using the adaptive thresholding method. On the upper plots, the activity counts and the state estimates of the Actiwatch are shown together. A voltage of 5 stands for high activity, 2.5 stands for transitions from activity to sleep and 0 stands for sleep. In the lower plots, the radar signals and state estimates are shown together using similar values.

It can be observed that there is significant agreement between the two sensing methods. The radar algorithm correctly detects restlessness during early morning sleep. However, at times during sleep, the radar might receive a weak signal and mistakenly transition to state #1.



(a)



(b)

Figure 6 The upper plots in (a) and (b) show the activity counts (normalized to 5) from the Actiwatch and the Actiwatch state estimates superimposed. 0, 2.5, and 5 values correspond to sleep, transitioning to sleep and active state estimates, respectively. The lower plots show the radar measurements (in Volts) and the radar state estimates superimposed. 0, 2.5, and 5 correspond to sleep, restlessness and low signal states, respectively. (a) Subject #1 and (b) Subject #3.

B. Comparing Radar Classifiers

Quantitatively comparing the performance of the two classification methods, we report the percentages of the states estimated by the radar analytics when 1) the Actiwatch estimates sleep, and 2) the Actiwatch does not estimate sleep. These values are listed in Table 1 for the three subjects. It can be observed that the radar and Actiwatch is mostly in agreement with both clustering methods. The k-means clustering yields a larger number of quiet state estimates (see Figure 4 and Figure 5) compared to thresholding. In addition, the adaptive *restless* thresholding method is more successful in determining restless periods than k-means clustering alone.

Table 1 Comparison of radar and Actiwatch state estimates for three subjects by using adaptive thresholding-based and k-means classifiers. R_{SLEEP}, $R_{RESTLESS}$, R_{QUIET} represent the percentages of the sleep, restless and quiet state estimates, respectively, from the radar analytics given that the Actiwatch does and does not estimate sleep.

Adaptive Thresholding						
	Actiwatch = Sleep			**Actiwatch ≠ Sleep**		
#	R_{SLEEP}	$R_{RESTLESS}$	R_{QUIET}	R_{SLEEP}	$R_{RESTLESS}$	R_{QUIET}
1	86.67	6.58	6.75	0.56	26.30	73.14
2	98.31	1.69	0	8.52	52.70	38.78
3	71.63	21.74	6.63	4.41	6.01	89.58
k-means						
	Actiwatch = Sleep			**Actiwatch ≠ Sleep**		
#	R_{SLEEP}	$R_{RESTLESS}$	R_{QUIET}	R_{SLEEP}	$R_{RESTLESS}$	R_{QUIET}
1	82.16	4.59	13.25	2.82	24.49	72.69
2	98.41	1.59	0	6.11	54.61	39.28
3	74.78	11.15	14.07	1.96	4.22	93.82

Finally, a receiver operating characteristic (ROC) graph comparing radar sleep results with actigraphy, for the various methods and cases, is shown in Figure 7. A true positive is defined as the case when the radar and Actiwatch both estimate sleep. Actigraphy is chosen as the ground truth because of its common role in sleep medicine [10]. It can again be seen that the two classifying methodologies are similar in performance and that the radar classifiers closely align with actigraphy-based results. However, it is important to note that Doppler radar may actually be more accurate in detecting true sleep (or daytime nap) intervals because waveform patterns can be examined directly, whereas

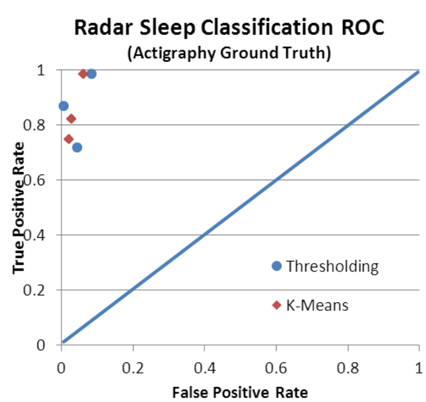


Figure 7 Radar ROC curve.

actigraphy estimates from motion only. Thus, the presented ROC is simply one viewpoint of radar performance.

V. DISCUSSIONS AND FUTURE WORK

A. Room environment sensors

Information from the remaining room sensors reinforces the radar sleep decisions. For instance, when the radar indicates that the person is in the bed possibly asleep, the sound and light sensors may help determine if the person is actually awake and watching TV from the bed. Example light and sound measurements are shown in Figure 8. The subject appears to turn off the light and sound (possibly TV) when going to sleep, but appears to remain restlessly in bed for several hours in the morning after both sound (possibly radio alarm) and light increase. The radar signal correctly captures the increased restlessness (as can be seen in Figure 6b).

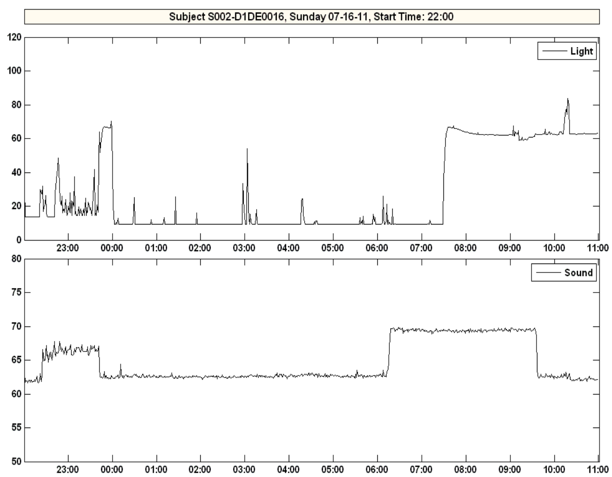


Figure 8 Light and sound measurements from Subject #3.

B. Fusion of results

Fusion of the various sensor features may help us make better sleep hygiene determinations. Constructing a state model might improve our decisions. For instance, an individual will generally pass through a restless state before falling asleep, and will once again pass through a restless state as he or she wakes up. Therefore, one would not expect the subject to transition directly from sleep to an empty bed, or in reverse. However, as an individual's sleeping position changes during the night, the radar signal may be reduced enough to mimic an empty bed signal. (This happens.) The state model can help in this instance by requiring more stringent transition conditions based on the time spent at a certain state, time of day, eventual known state, or including other sensors such as light and sound. For the reported examples, light and sound have been visually examined and considered. More research is needed in this area, especially for different subject populations. When available, actigraphy estimates can also factor into and improve overall sleep state decisions, ensuring the best metrics possible.

VI. CONCLUSION

Preliminary research shows that unobtrusive, sensor-based sleep monitoring can produce results similar to actigraphy-based methods when meaningful radar and sensor features are combined. Notably, the slope and intercept of a linear regression, fitted through the log-magnitude spectrum of a subject's sleeping radar signal, provides reliable features of sleep and recumbent restlessness. In an initial set of cases, two different methods, (k-means versus adaptive thresholding) were employed to properly classify subject sleep states.

Our research continually seeks to discover relevant and meaningful metrics of sleep quality in soldiers returning from combat with TBI and PTSD. The methods described in this paper will generate sleep health metrics for comparison with clinical assessments. Radar methods will be refined and their results fused with other sensors. Untethered and unobtrusive, sensor-based measures of sleep and sleep quality will be explored and recommended for adoption by sleep medicine, rehabilitation, and behavioral health professionals, particularly when working in the areas of telemedicine and potentially expensive treatment environments.

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