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Radar Monitoring in Sleep Medicine

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***Abstract*—An overnight sleep study can provide vital health diagnostics yet typically involves applying and monitoring multiple body-contact sensors, which can interfere with sleep and require cumbersome manual data analysis. Doppler radar technology has been demonstrated to provide a non-invasive means of measuring vital signs through clothing and bedding, including respiratory rate, heart rate, motion activity, body position, and tidal respiratory volume. This paper examines the potential for applying physiological radar to assess sleep apnea and intervention strategies.**

***Keywords*—Doppler radar, Sleep medicine, Obstructive sleep apnea, Sleep posture, Machine learning.**

I. Introduction

Both quality and quantity of sleep significantly impact learning, memory, metabolism, weight, safety, mood, cardio-vascular health, disease, and immune system function. Research indicates that 40 million Americans suffer from insomnia and chronic sleep disorders [1, 2]. Sleep and related breathing disorders can be divided into obstructive and central types. Obstructive Sleep Apnea (OSA), defined as absence of breathing despite respiratory effort, is the more common of the two, with an estimated 1.4 billion adults (aged 30-69) suffering globally from this disorder [3]. If OSA is suspected, diagnosis is confirmed with a "gold standard" sleep study, or polysomnogram (PSG), conducted overnight in an accredited sleep center. This involves measurement of several physiological parameters including brain activity (EEG), eye movements (EOG), muscle activity (EMG), cardiac function (ECG), blood-oxygen saturation, airflow (nose & mouth), and respiratory effort [4,5]. These measurements require a variety of encumbering wired sensors that come in contact with the patient's skin and impose discomfort and movement restrictions, which can adversely affect the quality of sleep. Sleeping in a supervised foreign environment also negatively impacts sleep quality. While existing FDA approved technologies for home sleep monitoring address some aspects of comfort and convenience, they still require sensors attached to the patient which negatively affect the opportunity and efficacy of monitoring [6]. There are commercially available wireless sleep monitors that are not medical devices such as ResMed S+ [7], based on UWB radar [8], and some proposed non-contact sleep apnea detection methods including FMCW sonar [9], and other radar configurations [10-11], but they are limited to simple respiratory rate/amplitude and actigraphy. While such measurements have been used successfully to detect central apnea as the absence of chest motion, their accuracy is limited in assessments for other apnea types, such as OSA, when chest motion is present without air exchange. Continuous-wave (CW) Doppler radar systems have the potential to provide accurate detection and assessment of the degree of OSA, based not only on relative amplitude of movement, but on advanced analysis of phase modulation of CW radar signals. Such analysis can distinguish chest motion that does not result in air exchange, as seen in OSA patients, from central apnea manifested as complete absence of chest motion.

There are many predisposing factors for OSA, and older adults have several factors from different domains affecting sleep [1]. Obesity, psychosocial factors, use of alcohol and/or use of sedatives, as well as certain anatomical features can all increase likelihood of OSA [12]. While severe OSA cases call for regular indefinite use of Continuous Positive Airway Pressure (CPAP) equipment [13] or surgery, the first line of treatment involves intervention through improved sleep hygiene. Recognized sleep hygiene procedures involve challenging lifestyle changes including control of unhealthy eating and self-medication habits, and adoption of beneficial sleep postures. It may not be difficult for patients to understand the purpose and logic of such directives, however it can still be extremely difficult to change such habits. Combined with modern learning algorithms, pervasive computing, and human-machine interface methods, smart wireless sleep monitors have potential to transform sleep medicine intervention to an individualized course of treatment

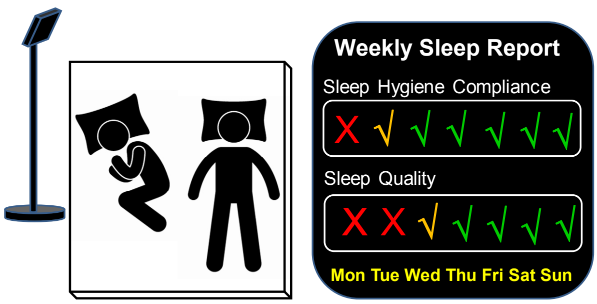

Fig. 1. In-home sleep monitor concept, and user interface. System logs sleep and events to assess intervention plan and incentivize adherence, and tailored app-based displays provide relevant feedback for patient and provider.

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in a natural home setting, which empowers patients and caregivers to jointly contribute to improved outcomes. Potentially, a novel non-contact bedside home monitoring system, capable of OSA assessment (Fig.1), can provide a patient with daily indicators of the correlation between adherence to doctor's orders and reduction in sleep apnea events.

Radar measurements are currently being explored for their potential is assessing various physiological responses associated with sleep monitoring. Some key features involve respiratory rate and volume, heart rate and variability, sleep stage, sleep posture, and respiratory obstruction. Various radar architectures and techniques have been applied for these applications along with both expert and data-driven machine learning signal analysis approaches.

II. Radar Measurement of Sleep Diagnostic Indicators

A. Respiratory Pattern

Doppler radar measurement of physiological motion has been demonstrated for monitoring rates, and tidal volume for respiration, and for the recognition of diagnostic respiratory motion patterns. Such measurements are typically achieved through the use of a microwave quadrature transceiver with dc-coupled output, connected to a digital data acquisition system for signal processing [14]. An example is shown in Fig. 2. A quadrature receiver can be used to overcome demodulation sensitivity to a target's distance which occurs in single channel direct conversion systems [15,16]. The in-phase (I) and quadrature phase shifted (Q) signals must be dc-coupled to the acquisition system to preserve information needed to avoid distortion and maintain displacement accuracy. Assuming the target's motion variation is given by Δx(t), the quadrature baseband outputs, assuming balanced channels, can be expressed as:

$$B_I = A_r \cos(\theta + 4\pi\Delta x(t)/\lambda)\,, \quad (1)$$

$$B_Q = A_r \sin(\theta + 4\pi\Delta x(t)/\lambda)\,, \quad (2)$$

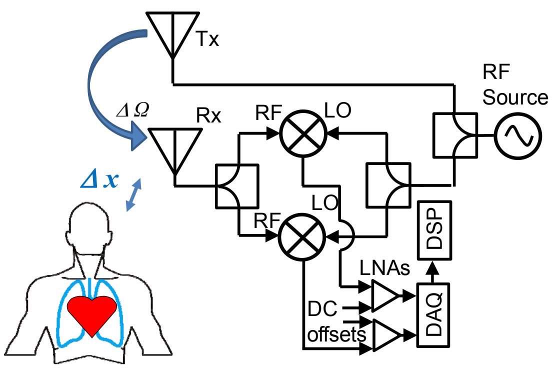


Fig. 2. Example diagram of a quadrature CW Doppler radar system used to measure physiological motion.

where θ is the constant phase shift related to the phase change at the surface of a target and the phase delay between the mixer and antenna. As shown in Fig. 3 (a), when there is only one source of periodic motion, and there is no signal distortion, the complex plot of quadrature outputs forms a fraction of a circle that has a radius of signal amplitude, A_r, with its center displaced by the dc offset of each channel. The dc offsets for each channel result from the finite port to port isolation of the transceiver as well as from clutter reflections and nominal subject displacement.

The exact phase demodulation can be performed using arctangent (non-linear) demodulation with center tracking [15,17]. The complex plot of the I and Q outputs depends both on received signal power and phase deviation due to a target's motion. From Eq. (1) and Eq. (2) received signal power becomes proportional to $A_r^{\,2}$, the square root of which is the radius of the arc formed by phase deviation due to the target's motion. Note the dc portion of the signal is composed of multiple components. The significant component (information) is contained only in the radius of the periodic arc, and components due to system leakage (internal), and clutter and nominal subject position (external) are extraneous, serving only to reduce arc measurement accuracy. Radar measurement of respiratory pattern has been used for applications including assessment of respiratory rate, tidal volume, and subject identity authentication [18, 19]. While tidal volume has been accurately inferred from torso displacement using a physical model approach, identity authentication has benefited significantly from machine learning approaches.

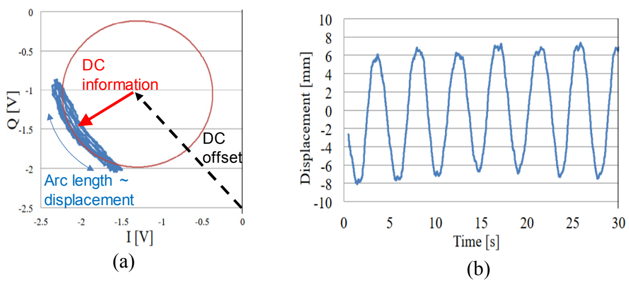


Fig. 3. I-Q constellation plot (a) and arctangent demodulation displacement plot (b) of CW Doppler radar measured respiratory motion.

B. Heart Pattern

While torso measurement is largely dependent on respiratory activity, heart activity can also be measured at the body surface using radar techniques. However, such measurements can be challenging under realistic conditions as the body motion due to heart activity is much smaller than that due to respiratory activity. Furthermore, while typical heart rates are significantly higher than respiratory rates, respiratory harmonics typically overlap with heart rate spectra making the two signals difficult to isolate, especially in the case of beat-to-beat analysis.

Radar measured average heart rate has been demonstrated at a 1-m distance using only 20 nW [20], and at distances of up to 21 m [21] using less than 100 milliwatts. Heart rate variability (HRV) has also been accurately measured in the presence of significant interfering respiratory harmonics using a wavelet filter approach [22].

C. Sleep Posture

Throughout a night of sleep, a subject may assume different recumbent postures in bed which can be roughly characterized as prone, supine, and side. Measurement of cardiopulmonary activity is affected by this posture, and diagnostic model efficacy can be enhanced by posture recognition. In fact, the physical model associating torso displacement with respiratory tidal volume depends explicitly on the orientation of the body with respect to the supporting surface and to the direction of propagation of the radar signal.

For example, a subject taking in a certain tidal volume [23] produces a different torso displacement under different postures, causing an erroneous assessment if the change in posture is not recognized. There are two primary mechanisms by which position affects radar measurements. First, due to the asymmetric shape of the body parts which move with respiration, switching position creates a different effective radar cross section (ERCS) observation. The ERCS is similar to the physical RCS, but only relates to the moving portion of the subject's body. Second, the way the body weight interacts with the bed at each position will affect the displacement magnitude of the torso during respiration.

Comparison of ERCS values and displacement magnitudes measured at three sleeping positions reveals trends. It has been demonstrated that ERCS obtained in the prone position is generally greater than that in supine position, and ERCS in side position is smaller than that in supine [24]. This is basically due to the full area of the back moving with respiration in the prone position, while only a localized pulmonary region moves in the supine position, and the entire physical cross section of the side is smallest no matter how much of it moves.

A simplified illustration of the principles used in radar-based sleep posture recognition is shown in Fig. 4. Accurate assessment has been demonstrated both with a supine-calibrated physical model-based system [25], and a calibration-free machine learning based system [26]. Other systems have relied on the use of a deep neural network with prior calibration knowledge [27,28].

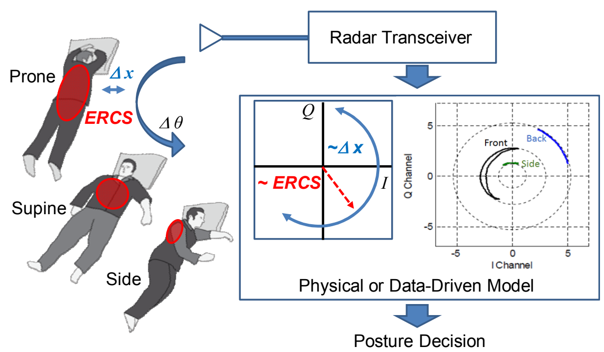


Fig. 4. Illustration of sleep posture recognition system. Effective radar cross-section (ERCS) and length of phase arc are measured by radar and a physical or data-driven model uses this data to determine sleep posture.

D. Sleep Stage

Another important measure in sleep medicine is the determination of sleep and sleep-stage. Doppler radar cardiopulmonary monitoring using a quadrature transceiver provides a means for distinguishing sedentary heart and respiratory activity from other body motion, through the assessment of the stability of a constant arc radius during respiratory displacement. That is to say, a constant radius means that the subject's motion is only that due to cyclic respiration. This measurement thus provides a basic measure of the sleep/wake state as well as a measure of actigraphy.

However, it is also desirable to recognize distinct stages of sleep including REM, light sleep, and deep sleep. A continuous-wave (CW) Doppler radar based on machine learning system using the bagged trees algorithm has been used to classify the four stages of wake/sleep. Nine features were extracted for four classifiers to classify the stages, and experimental results showed an accuracy of 78.6% compared to the PSG [29].

E. Respiratory Obstruction

Ultimately, and effective sleep monitoring system must also provide an accurate measurement of respiratory obstruction events during sleep. Obstructive sleep apnea (OSA) is typically identified using two respiratory effort belts, one placed around the chest and the other around the abdomen [30]. During OSA, respiratory effort is out of phase in the two positions, and there is no air flow. This is known as paradoxical breathing. With paradoxical breathing, the abdomen and rib cage move in opposite directions rather than in unison: when the rib cage expands, the abdomen contracts, and when the abdomen expands, the rib cage contracts, while the airway is blocked. OSA is commonly defined as an 80-100% reduction in airflow signal amplitude for a minimum of 10 seconds with continued respiratory effort. Hypopneas are characterized by a 50% reduction in air flow for more than 10 seconds, followed by arousal. The Apnea-Hypopnea Index (AHI) is expressed as the number of apneas and hypopneas per hour of sleep.

While it is possible to use two separate radars to target the thorax and abdomen independently [31], this approach is constrained by strict aiming and coordination constraints which greatly limit freedom of movement. A single microwave Doppler radar can illuminate the whole body at once, and the detected signal will be the sum of signals reflected from different thorax/abdomen areas that are positioned at slightly different distances from the antenna. If we assume the whole body surface moves in phase, the signals from different parts of the body will add constructively or destructively (resulting in larger or smaller arc radius), but always resulting in one clean arc, as indicated in Fig. 3(a). Multiple signal sources will result in reflected signals delayed tens of nanoseconds, which is insignificant compared to the physiological signal, and therefore does not affect the complex constellation, as long as all sources of motion (for respiration, chest and abdomen) are moving simultaneously and in phase. Thus the total baseband signal is found as:

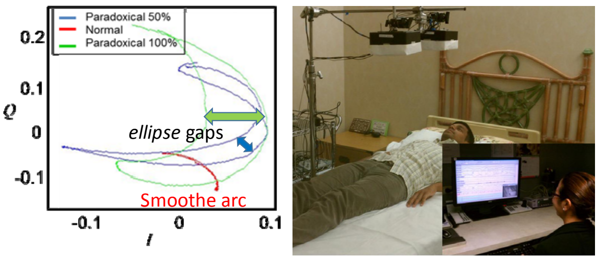
$$B = \sum \exp(j(\phi_n + \Delta p(t))) + DC_n \ , \qquad (3)$$

where DC_n is the dc offset associated with the path length for each source, and ϕ_n is phase delay associated with the path length for each source. However, when different body parts are moving at the same frequency but out of phase or with a phase delay, the signals with different phases will add to distort the shape of the complex constellation. The resulting baseband signal can be found as:

$$B = \sum \exp(j(\phi_n + \Delta p(t - \theta_n))) + DC_n \ , \qquad (4)$$

where θ_n is the phase delay between the sources.

Based on these complex constellation properties, the degree of paradoxical breathing can be quantified by estimating the ratio of principle and the secondary vectors of the quadrature signals' covariance matrix. The degree of periodicity of the baseband signals can be estimated to differentiate a paradoxical breathing signal from a random motion signal.



(a) (b)

Fig. 5. Radar measurement of simulated paradoxical breathing(a) and set up for preliminary study of OSA assessment for ten patients (b). Arcs produced by a phantom simulating different degrees of paradoxical breathing clearly show distinct shape change (ellipse gaps) for 50% or 100% out-of-phase motion (b). The sleep study validated the physical model for recognition of a non-specific OSA event (b)[32].

When the breathing is all in-phase (normal), the complex signal is an arc of mostly uniform radius, with a smaller per-cycle deviation than the complete elliptical shape occurring when breathing is out-of-phase (apnea). Also, the degree of signal periodicity can be combined with respiration and motion monitoring software to provide a paradoxical breathing indicator that differentiates a signal due to paradoxical breathing signal from a signal caused by random motion.

Doppler radar measurements of a mechanical phantom designed to simulate respiration and paradoxical breathing are shown in Fig. 5(a). The plot clearly depicts the presence of paradoxical breathing through degrees of trace ellipticity. Here a smooth narrow arc forms during normal breathing (red trace). The trace distorts to become a broader ellipse when the simulated abdomen moves out of phase with the simulated thorax (blue-50%, and green-100%). The challenge for practical application is to produce high precision radar hardware that can accurately capture physiological motion without introducing distortion that could be misinterpreted as out of phase motion. In addition, novel algorithms are required to detect this feature automatically, and to distinguish it from arc distortion due to random motion. Indication of the degree to which the abdomen and thorax move out of phase provides the physician with information on the presence of OSA, but still allows the physician to apply experience based judgment for diagnosis. Clinical results have been presented [32].

III. Conclusion

Automated non-contact sleep measurement systems could be a powerful tool for improving sleep medicine and practices and extending sleep assessment availability. They can provide the basis for long term at home monitoring to facilitate diagnostics based on individualized data as part of the Internet of Things remote healthcare services. For this to happen, development of a practical sensor system with built in diagnostics and user friendly interface and feedback experience must be studied and realized. Doppler radar systems leveraging physical and data driven signal processing algorithms have the potential to form accurate sleep monitoring systems which can provide specific feedback useful to sleep medicine patients trying to adopt new more effective sleep hygiene.

IV. Acknowledgement

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