Obstructive Sleep Apnea (OSA) Events Classification by Effective Radar Cross Section (ERCS) Method Using Microwave Doppler Radar and Machine Learning Classifier

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***Abstract*— In-home sleep monitoring system using Microwave Doppler radar is gaining attention as it is unobtrusive and non-contact form of measurement. Most of the reported results in literature focused on utilizing radar-reflected signal amplitude to recognize Obstructive sleep apnea (OSA) events which requires iterative analysis and cannot recommend about sleep positions also (supine, prone and side). In this paper, we propose a new, robust and automated ERCS-based (Effective Radar Cross section) method for classifying OSA events (normal, apnea and hypopnea) by integrating radar system in a clinical setup. In our prior attempt, ERCS has been proven versatile method to recognize different sleep postures. We also employed two different machine learning classifiers (K-nearest neighbor (KNN) and Support Vector machine (SVM) to recognize OSA events from radar captured ERCS and breathing rate measurement from five different patients' clinical study. SVM with quadratic kernel outperformed with other classifiers with an accuracy of 96.7 % for recognizing different OSA events. The proposed system has several potential applications in healthcare, continuous monitoring and security/surveillance applications.**

Keywords*— *Sleep apnea classification, Doppler radar, ERCS, Wireless monitoring

I. INTRODUCTION

Obstructive Sleep Apnea (OSA) is a sleeping disorder which causes breathing difficulty during sleep. As defined in American Academy of Sleep Medicine (AASM), apnea presents a 90% or more reduction in airflow compared to the normal baseline, while hypopnea presents a 70% or more reduction accompanied by more than 3% oxygen desaturation or arousal [2]. OSA is linked with cardiovascular disease like coronary heart disease, heart failure, atrial fibrillation, morbidity of hypertension and arrhythmia [1]. Polysomnography (PSG) is considered as gold standard for sleep apnea diagnosis which is carried out overnight in a specialized hospital-based sleep laboratory [3] with dedicated contact sensors and need a sleep technician. It is uncomfortable, expensive and the medical facilities have a small number of sleep technicians, leading to long waiting lists [5]. To guarantee natural conditions sleep monitoring, non-contact home monitoring technology is emerged. Recently, smartphone is used to identify apnea event from acoustic sound during breathing but failed to identify many hypopnea events accompanied with snoring properly [4]. Other contactless technology is using infrared cameras but its computationally difficult, privacy concern and efficiency decreases during apnea event compared to normal breathing and movement [6]. Prior research also demonstrated the feasibility of utilizing Doppler radar system to identify different apnea events in comparison to PSG system [5]. However, that proposed system was not automatic as the system utilizes the amplitude-based technique to find different apnea events which requires extensive analysis [5]. In addition to that, ERCS has been utilized to recognize different sleep positions (supine, prone and side) [7]. It has been proved in various investigations that subject sleep positions play an important role in sleep quality and avoidance of certain sleeping position like supine may lead to decrease in the number and severity of obstructive episodes [8]. Thus, a uniform, effective and automatic method is required which can determine sleep positions and sleep apnea events also to make the system robust.

In this paper, we investigated the feasibility of ERCS method for recognizing different OSA events (normal, apnea and hypopnea) from the clinical study with five different participants utilizing microwave Doppler radar system. In addition to that, we also integrated two different machine learning classifiers (KNN, SVM) to recognize different OSA events from ERCS and breathing rate measurement of the participants from different episodes of the clinical study. SVM with quadratic kernel outperformed other classifier with an accuracy of 96.7%. The proposed system has several potential applications especially in in-home sleep monitoring system for adults and infants also (Sudden Infant Death Syndrome).

II. THEORY

A. PRMS monitoring System

Non-contact and non-invasive physiological radar monitoring system (PRMS) includes 2.4GHz and 24GHz radar. For this paper, only data from 2.4GHz radar is analyzed. The distance between the antenna board and the patient s chest was approximately 1m as the nearest safe distance without obstructing the patient movement.

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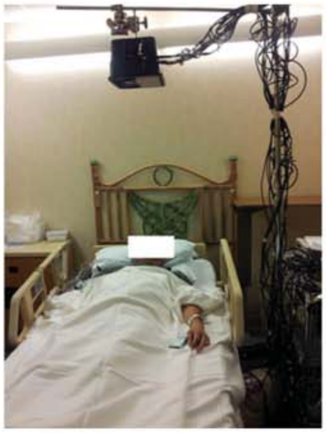

Fig. 1. Experimental setup & schematic diagram for PRMS [5]

Five volunteers with known OSA were recruited for this study. The complete experiment setup and schematic diagram are shown in Fig. 1.

B. Effective radar cross section

The measure of the power of the wave bouncing off a radar target with respect to the incident one is defined as the radar cross section (RCS). In human cardiopulmonary testing, the target is the surface of the torso moving due to respiration and heartbeat and results in an effective radar cross section (ERCS) [7]. OSA is associated with airway collapse due to throat muscle relaxation during sleep. The movement of the human torso during respiration varies from person to person and with depth. When there is an obstruction in the airway, paradoxical breathing occurs, and different parts of the torso move out of phase. ERCS correlates with the amount of air flowing into the body during inhalation, namely the tidal volume of respiration. During OSA, power from moving surface of torso changes for change in tidal volume which is reflected in ERCS. During normal breathing, apnea, and hypopnea, ERCS will be different due to different movement contributions from abdomen and thorax. The equation to calculate effective radar cross section, σ from all radar measurement parameter is:

$$\sigma = \frac{R^4}{Pin} \times \frac{1}{\Re} \times \left(\frac{A}{G}\right)^2 \tag{1}$$

where A is radius of Arc, □ includes all fixed loss in the system, G is Low noise amplifier gain, P_{in} is input power, R is range of the radar.

C. Feature extraction algorithm

The datasets are collected from the sleep study center using PRMS monitoring setup for five OSA patients with 128 Hz sampling frequency. Sandman data was scored using respiratory rules for adults stated in AASM manual by sleep-technician which is our reference [5]. For OSA event classification, two feature named breathing rate and square of radius of arc are extracted from the radar output, the process is depicted in Fig 2. It is evident from (1) that, for a certain setup ERCS is directly proportional to square of radius of arc, A where all other parameters are constant in that setup. That s why variation of square of radius of arc, A is considered here as a feature to classify OSA events. The unwanted body movement is separated from radar output as these are several magnitudes larger than chest movement data. The categorized I/Q data is then imbalance compensated. The breathing rate of different OSA events from radar output data are calculated using Fast Fourier algorithm. Fig 4 represents FFT of I/Q data of OSA events.

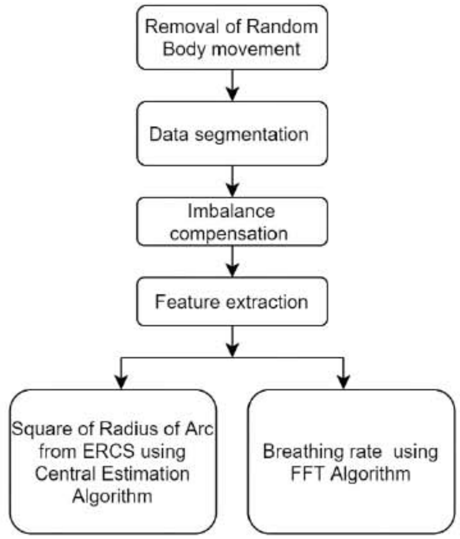

Fig 2: Flow chart for Feature Extraction Algorithm

For second feature extraction, center estimation algorithm on radar output data is used to get radius of Arc, A corresponding to apnea, normal and hypopnea events. In practical Doppler radar testing, the acquired baseband signal is subject to dc offset due to reflection from stationary clutter. This causes the arc traced by the in-phase and quadrature channels to be offset from the origin of the plot [7]. The role of the center estimation algorithm is to locate the circle to which the arc belongs and bring the center of the circle to the origin of the complex I-Q plot. The result of the algorithm is shown in Fig 3 for different OSA events.

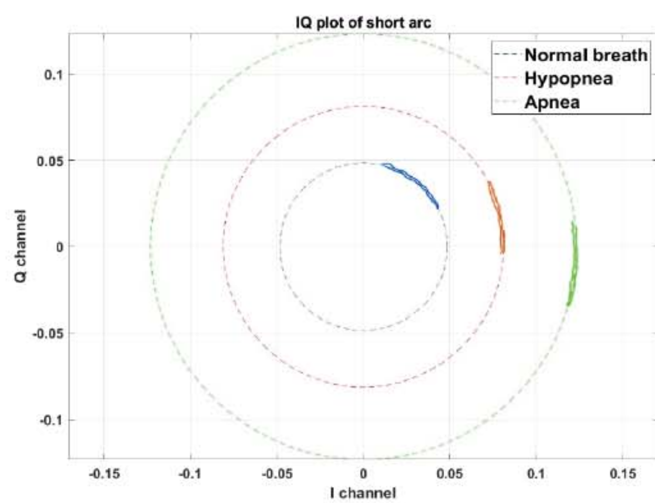

Fig 3: Central Estimation Algorithm tracked arc on circle drawn from different radius of arc, A for OSA patient in different OSA events (Normal, Hypopnea, Apnea), here square of Radius of Arc is directly proportional to ERCS

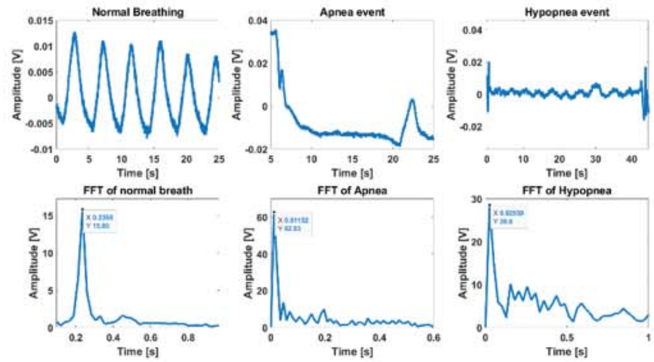

Fig 4: I/Q plot and corresponding Fast Fourier Transformation result of different OSA events (Normal, Hypopnea, and Apnea)

D. Machine Learning Classifiers:

We integrated two different popular machine learning classifiers, K-nearest neighbor (KNN) and Support Vector Machine [9]. KNN is distance-based classification process whereas SVM is hyperplane-based classification approach [9]. We integrated two different kernel functions (Linear and Quadratic) which is used to mapping the non-linear function into linear mapping [9].

III. Result

The data from all patients are analyzed in MATLAB (R2018b, The Math Works Inc., Natick, MA). In order to test performance of our integrated classifiers (KNN, SVM) a total set of 30 data set of each having 60 s epoch having three different patterns from five different participants. Table-I above shows the classification accuracy for different classifiers.

TABLE I
ACCURACIES FOR DIFFERENT CLASSIFIERS

Classifiers	Training Accuracy	Test Accuracy
KNN (1 Neighbor)	91%	89.2%
SVM (Linear)	96.67%	94.2%
SVM (Quadratic)	98.67%	96.7%

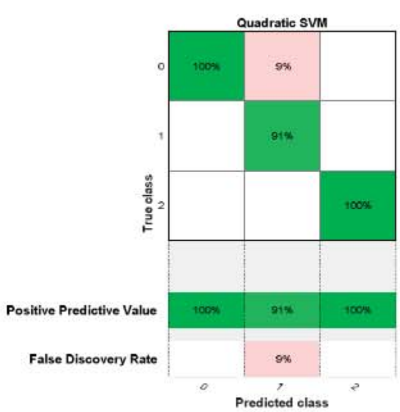

Fig. 5: Confusion Matrix for Cubic SVM with respiration traces for ERCS and breathing rate measurement. (Class 0 represents normal breathing, class 1 apnea event and class 2 hypopnea event.

Testing data set is different than training data set, where 60% data set were used for training and 40% data set were used for testing. SVM with quadratic kernel function shows the best accuracy of 96.7% which outperformed other classifiers also. The confusion matrix of the testing data set is shown in Fig. 5.

IV. Conclusion

In this paper, we tested the efficacy of ERCS methods to classify OSA events using Microwave Doppler radar which is integrated with machine learning classifier. The experimental result demonstrated that, SVM with quadratic kernel outperformed KNN classifier with an accuracy of 96.7% to classify OSA events. As PSG system was used, the patients were sleeping in supine position. Since ERCS changes with sleep position, if sleep position changes, sleep apnea classification based on ERCS will be a more complex problem. Deep learning method will be investigated to solve this problem.

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