

Identity Authentication of OSA Patients Using Microwave Doppler radar and Machine Learning Classifiers

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Abstract — Non-contact home-based sleep monitoring will bring a paradigm shift to diagnosis and treatment of Obstructive Sleep Apnea (OSA) as it can facilitate easier access to specialized care in order to reach a much boarder set of patients. However, current remote unattended sleep studies are mostly contact sensor based and test results are sometimes falsified by sleep-critical job holders (driver, airline pilots) due to fear of potential job loss. In this work, we investigated identity authentication of patients with OSA symptoms based on extracting respiratory features (peak power spectral density, packing density and linear envelop error) from radar captured paradoxical breathing patterns in a small-scale clinical sleep study integrating three different machine learning classifiers (Support Vector Machine (SVM), K-nearest neighbor (KNN), Random forest). The proposed OSA-based authentication method was tested and validated for five OSA patients with 93.75% accuracy using KNN classifier which outperformed other classifiers.

Index Terms — Sleep Apnea, SVM, KNN Classifier, Authentication, Radar.

I. INTRODUCTION

Obstructive sleep apnea (OSA) is a highly prevalent sleep disorder and yet also among the most frequently underdiagnosed health problems [1]. To date, Polysomnography (PSG) is the most common and established screening technique which is carried out in a specialized hospital-based sleep laboratory [2]. PSG test requires dedicated sleep laboratories where patients need to go overnight screening with dedicated contact sensors and a sleep technician need to coordinate all these sensors [3]. Recently, portable in home sleep monitoring devices have become an accepted alternative for screening OSA due to discomfort, expense and associated delay of PSG in sleep laboratories [4]. One major area of concern for unattended remote sleep studies is falsification sleep test data by substituting another individual for the test, especially for sleep-critical job holders like professional drivers, and pilots [5]. This typically results from fear of imposed lifestyle change, or possible punitive action that may come with by a positive diagnosis of a sleep disorder [4-5]. Thus, a robust unattended remote wireless OSA monitoring system which can function reliably outside of a controlled sleep center; must include identity verification for the monitored subject [4-5]. Prior research demonstrated the efficacy of integrating a fingertip sensor with home sleep apnea testing equipment for biometric verification during

home sleep studies [9]. However, attachment of a fingertip pulse oximeter sensor for authentication creates extra burden and discomfort during remote unattended sleep monitoring [4-5]. Moreover, there has been research on the identification of persons based on sedentary breathing patterns and the feasibility of Doppler radar based non-contact authentication has been tested and verified based on normal breathing patterns [6-9].

In this study, we propose an expert system for automated recognition of patients with OSA symptoms using a non-contact physiological radar monitoring system. Our proposed expert recognition system consists of non-contact Doppler radar system integrated with three different machine learning classifiers to recognize five different patients based on their radar captured breathing pattern from an overnight clinical study in a sleep center.

II. MATERIALS & METHODS

The PRMS monitoring system includes 2.4 GHz and 24 GHz radar to achieve high sensitivity and high resolution. A commercial off the shelf K-MC1 module from RFbeam microwave was used as 24 GHz radar. This module has K-band antenna with I/Q mixer and IF-preamplifiers. Coaxial components were used to implement 2.45 GHz Doppler radar. The overall experimental setup and efficacy of the system has been illustrated in Fig. 1 [10]. The complete experiment setup is shown in Fig. 2. During the test, the

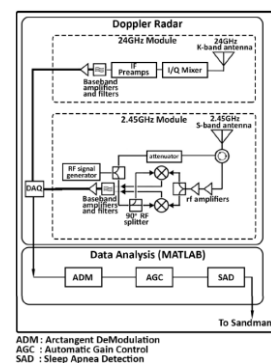


Fig. 1. Schematic of physiological radar monitoring system (PRMS) used in this experiment.

was also monitored remotely from an observation room. The distance between the antenna board and the patient's chest was approximately one meter as the nearest safe distance without obstructing the patient movement. The study was approved by the Institutional Review Board (IRB). 5 volunteers with known OSA were recruited for this study and provided with written consent prior to the study. The participants were not allowed to use CPAP during the tests.

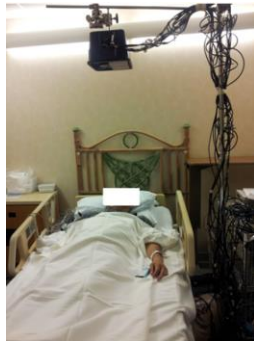


Fig. 2. Experiment setup for sleep disorder monitoring.

III. RESULTS

The datasets shown are respiration traces collected from the sleep study center using PRMS monitoring setup for five OSA patients with 100 Hz sampling frequency. The breathing pattern captured in the I/Q channel for the first volunteer is shown in Fig. 3 below depicts the captured breathing pattern from Radar for the first volunteer.

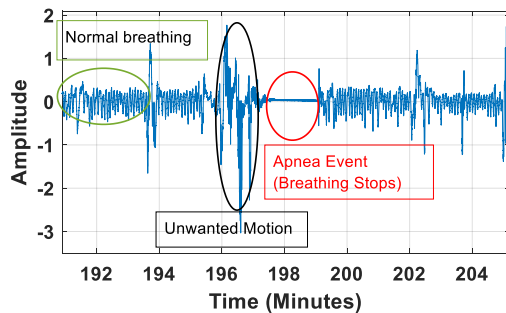


Fig. 3. Radar captured breathing pattern of a volunteer having OSA. The red circle shows the apnea event which illustrates the pause in breathing pattern clearly corresponds to the occurrence of OSA.

If the radar output signal from unwanted body movement is several magnitudes larger than breathing the locomotion will be discarded. After removing DC offset we have utilized linear demodulation in order to find accurate chest displacement from captured I/Q channel signals. Linear

demodulation is a technique which uses Eigen value decomposition of the covariance matrix of I/Q channel signal then projection/selection of the major components [6] [10]. Fig. 4 below depicts linear demodulated signals for four different participants.

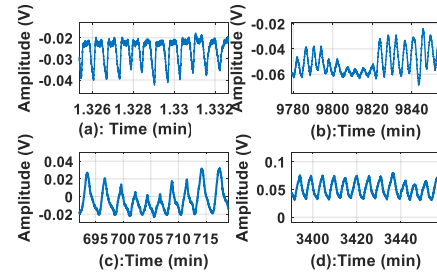


Fig. 4. Linearly demodulated signal for four different subjects.

A. Respiratory feature extraction:

Extracted respiratory features are for 60 s epoch with 100 Hz sampling frequency. Extracted features are described below

1. Peak power spectral density: The power spectral density describes how the power of a signal is distributed over frequencies.
2. Packing density: The difference in inspiratory and expiratory duration within that segment from person to person could be identified by a parameter called packing density.
3. Linear Envelop Error of the peaks: By observing respiration signal within that segment there is variation within the peaks. These peaks shows variations for five different patients.

After determining the local maximum points, a linear fit is determined. Fig. 5 below illustrates the respiratory features extracted from radar captured respiration pattern.

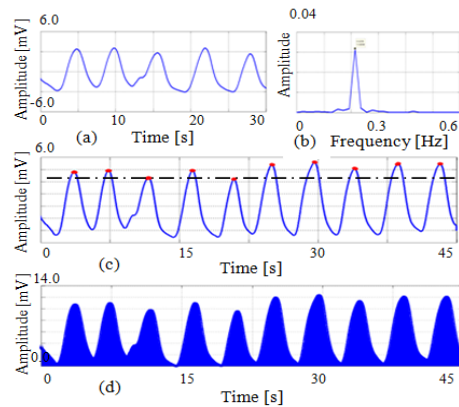


Fig. 5. Epoch features are illustrated (a) Time series of respiration trace (b) peak power spectral density (breathing rate within that segment) (c) Distribution of peaks in time domain (d) Linear envelop error of the peaks in time domain.

It has also been observed that there is significant differences of these three respiratory features. Table-I below illustrates the unique features of OSA patients.

B. Machine Learning Classifiers:

We have employed three different supervised machine learning algorithms to train and test the unique features data set of OSA patients. K-nearest neighbor (KNN) is the simplest among all machine learning algorithm. KNN algorithm uses distance based metric (Euclidean distance and hamming distance) to classify different variables [11].

Table-I
Unique Feature Extraction

Freq of max PSD (Hz)	Packing Density	Linear Envelop Error of FFT coefficients	OSA Patients
.213298	.521341	.170702	P1
.191968	.517554	.038110	P1
.213298	.406263	.010226	P1
.....			
.272787	.312932	.19954	P2
.277287	.369265	.067173	P2
.234627	.354366	.090660	P2
.....			
.234628	.499702	.275350	P3
.213298	.521341	.170702	P3
.191968	.418306	.013663	P3

In order to test the performance of our integrated classifier a total of 50 sets of data each having 60 s epoch were collected from five OSA patients. 60% of this dataset was used for training and then 40% of the dataset was tested to verify the classification task. The training dataset and test dataset was different to verify either our proposed expert system can accurately identify different patients uniquely or not. The resulting accuracies for different classifiers are shown below in Table-II. The KNN classifier outperforms other classifier like SVM and random forest. We have used

different number of neighbors for KNN classifier and got the best result for one neighbor. Fig. 6 below represents the confusion matrix for test data set. In testing data set, overall 16 times attempts were made to classify different participants based on their extracted unique features dataset (FFT peaks, linear regression error of the peaks, packing density). Participant-1 was classified accurately 3 times, participant-2 was classified accurately 2 times, participant-3 2 times, participant-4 2 times and participant-5 6 times was classified accurately. However, there is one misclassification. Participant-4 misclassified once as participant-5. The overall classification accuracy for testing data set is also 93.75%.

TABLE II
ACCURACIES FOR DIFFERENT CLASSIFIERS

Classifiers	Training Accuracy	Test Accuracy
KNN (1 Neighbor)	100%	93.75%
SVM (Radial basis function)	91.67%	84.38%
Random forest	91.67%	90.63%

IV. CONCLUSION

The purpose of this study was to test the efficacy of a non-contact wireless expert continuous authentication system for automated recognition of patients with OSA. Thus, we explored the applicability of our proposed non-contact wireless recognition system in identifying people with OSA symptoms. The feasibility of unique feature extractions with three different classification algorithms was tested and verified. The system automatically recognized five different patients based on their irregular breathing patterns captured with radar in a clinical study.

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Confusion Matrix for Testing Dataset with OSA Symptoms						
P1	3 18.75%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	3 100%
P2	0 0.0%	2 12.50%	0 0.0%	0 0.0%	0 0.0%	2 100%
P3	0 0.0%	0 0.0%	2 12.50%	0 0.0%	0 0.0%	2 100.0%
P4	0 0.0%	0 0.0%	0 0.0%	2 12.50%	1 6.25%	3 66.67%
P5	0 0.0%	0 0.0%	0 0.0%	0 0.0%	6 37.50%	6 100%
Patient-1	3 100%	2 100%	2 100%	2 100%	7 85.71%	16 93.75%
Patient-2	0 0.0%	2 100%	0 0.0%	0 0.0%	0 0.0%	2 100%
Patient-3	0 0.0%	0 0.0%	2 100%	0 0.0%	0 0.0%	2 100%
Patient-4	0 0.0%	0 0.0%	0 0.0%	2 100%	1 50.0%	3 66.67%
Patient-5	0 0.0%	0 0.0%	0 0.0%	0 0.0%	6 100%	6 100%
True class	3	2	2	2	6	16

Fig. 6. Confusion matrix of KNN classifier for testing respiration traces. The diagonal position of the matrix represents the number of OSA patients classified accurately.

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