Radar-Based Automatic Detection of Sleep Apnea Using Support Vector Machine

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***Abstract*—Early diagnosis of sleep-apnea-related breathing problems helps to avoid the increased risk they can cause. In this study, we performed simultaneous radar measurements and polysomnography on patients with sleep apnea. A support vector machine algorithm was applied to the radar data to automatically detect sleep apnea events. Support vector machine parameters were optimized using the relationship between the radar and polysomnography data. The support vector machine was found to be effective in noncontact detection of central/mixed sleep apnea events using radar data. The proposed approach achieved an accuracy of 79.5%, a recall of 71.2%, and a precision of 71.2%.**

***Keywords*—Millimeter-wave radar, support vector machine, sleep apnea, detection.**

I. Introduction

Because sleep apnea increases the risk of developing serious health problems, the early diagnosis of sleep apnea is important. Although polysomnography (PSG) is currently the gold standard for diagnosing sleep apnea, PSG requires that numerous sensors be attached to the patient, which can have a psychological effect on the test results. For this reason, noncontact radar-based measurement is promising. Previous studies have used radar systems for the noncontact detection of sleep apnea events [1]-[6]. However, most did not use machine learning algorithms for event detection [6], and did not compare the accuracy of detecting different types of sleep apnea. In addition, most studies used time-domain features for event detection, whereas frequency-domain features have been rarely used. We propose a new approach using a support vector machine (SVM) applied to the time-frequency distribution of the radar signal. We evaluate the accuracy of the proposed approach in detecting sleep apnea events of different two types.

II. Classification Using Machine Learning

A. Support Vector Machine

SVMs are machine learning algorithms based on supervised learning. An SVM generates a boundary surface that classifies input data using support vectors. In this study, we used a two-class (normal breathing and sleep apnea) classifier. Note that, for simplicity in this paper, both sleep apnea and hypopnea events are referred to as sleep apnea events. We used a quadratic polynomial kernel in the SVM algorithm to allow for nonlinear separation of the two classes in the input vector space.

B. Radar Signal Processing

We used a 24-GHz millimeter-wave radar system, a standing wave radar which has 180 MHz bandwidth, and PSG simultaneously on patients ($n = 2$) with sleep apnea symptoms sleeping overnight in the hospital (Fig. 1). We applied a short-time Fourier transform to the radar signal $s(t)$ to generate a spectrogram $S(t, f)$, where -30 s $\leq t \leq 30$ s and $0 \leq f \leq 0.5$ Hz. Each spectrogram was downsampled to a 20×30-pixel low-resolution image, which was then converted to 600-dimensional vectors that were used as input to the SVM. A vector was generated every 5 s and labeled 0 or 1, denoting normal breathing and sleep apnea, respectively. More precisely, if a sleep apnea event was detected at the center of a 60 s window, the vector was labeled 1, which allowed us to detect the precise time of a sleep apnea event. The vector data set was divided into vectors for training the SVM and vectors for evaluating classification performance of the SVM. The vectors in the training and testing sets did not overlap.

III. Evaluation of Apnea Detection Accuracy

Patients A and B had obstructive sleep apnea (OSA) and central/mixed sleep apnea (CSA), respectively. Radar measurements and PSG were conducted for seven hours on each patient. For patients A and B, 206 and 280 sleep apnea events were detected, respectively. The upper panels of Figs. 2 and 3 show the real (black) and imaginary parts (red) of the radar signal echoes; sleep apnea segments manually detected by PSG technicians are shown with black rectangular outlines. The lower panels of Figs. 2 and 3 show sleep apnea events detected from the radar signals using the SVM algorithm. Tables I and II show confusion matrices for OSA and CSA sleep apnea event detections, respectively. The CSA events of patient B were able to be detected with a higher accuracy than that of the OSA event detection for patient A. Accuracies were 79.2% and 79.5%, recalls were 36.1% and 63.3%, and precisions were 40.8% and 71.2% for patients A (OSA) and B

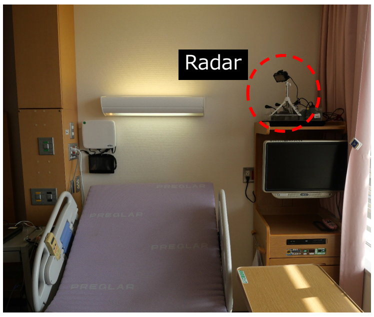

Fig. 1. Millimeter-wave radar installed in the hospital room.

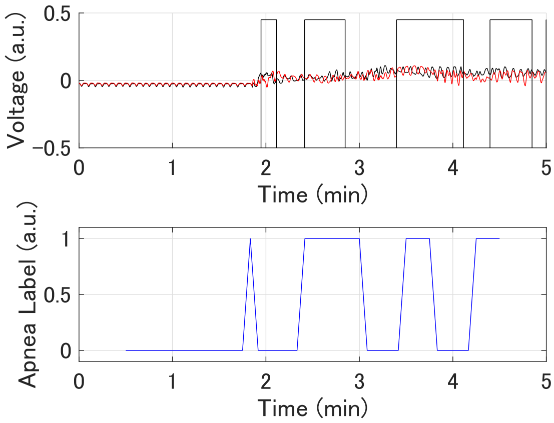

Fig. 2. Radar echoes from patient A with manually detected sleep apnea events (top), and sleep apnea events detected from the radar signal using the proposed method (bottom).

(CSA), respectively, using the proposed sleep apnea detection method.

IV. Conclusion

We proposed an approach using an SVM algorithm that can automatically detect sleep apnea events using radar-based

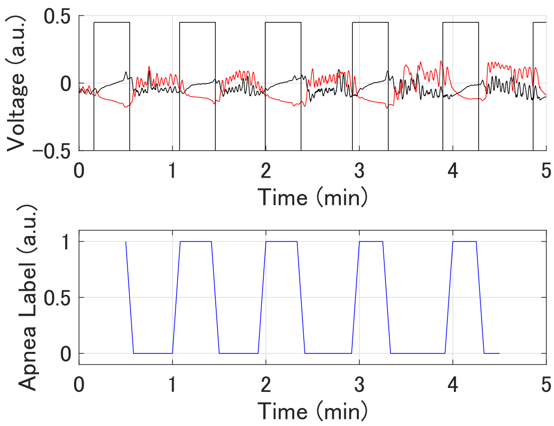

Fig. 3. Radar echoes from patient B with manually detected sleep apnea events (top), and sleep apnea events detected from the radar signal using the proposed method (bottom).

TABLE I
Confusion Matrix for the Detection of OSA Events Using Radar and SVM

		Estimated	
		Apnea	Normal
Actual	Apnea	265	470
	Normal	385	2996

TABLE II
Confusion Matrix for the Detection of CSA Events Using Radar and SVM

		Estimated	
		Apnea	Normal
Actual	Apnea	858	478
	Normal	347	2413

noncontact measurements. We performed simultaneous measurements on each patient using a radar system and PSG. The results showed that CSA events were accurately detected using the proposed method, whereas OSA events were more difficult to detect. We plan to conduct measurements on additional patients to clarify what types of sleep apnea can be accurately detected using the radar-based automatic detection.

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