Noncontact Detection of Sleep Apnea Using Radar and Expectation–Maximization Algorithm

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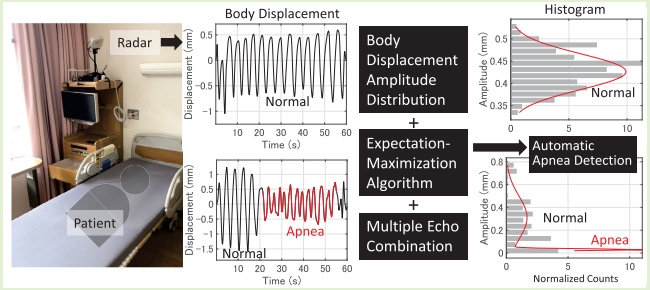
***Abstract*—Sleep apnea syndrome (SAS) requires early diagnosis because this syndrome can lead to a variety of health problems. If sleep apnea (SA) events can be detected in a noncontact manner using radar, we can then avoid the discomfort caused by the contact-type sensors that are used in conventional polysomnography (PSG). This study proposes a novel radar-based method for accurate detection of SA events. The proposed method uses the expectation–maximization (EM) algorithm to extract the respiratory features that form normal and abnormal breathing patterns, resulting in an adaptive apnea detection capability without any requirement for empirical parameters. We conducted an experimental quantitative evaluation of the proposed method by performing PSG and radar measurements simultaneously in five patients with the symptoms of SAS. Through these experiments, we show that the proposed method can detect the number of apnea and hypopnea events per hour with an error of 4.8 times/h; this represents an improvement in the accuracy by 1.8 times when compared with the conventional threshold-based method and demonstrates the effectiveness of our proposed method.**



***Index Terms*— Antenna arrays, biomedical engineering, Doppler radar, radar measurements, radar signal processing.**

I. Introduction

THE number of adults aged from 30 to 69 years that display moderate to severe symptoms of sleep apnea syndrome (SAS) is estimated to be approximately 425 million worldwide [1], [2]. SAS is known to increase the risk of complications, such as hypertension, coronary artery disease, and cerebrovascular disease and can also lead to work-related errors and traffic accidents because of daytime sleepiness and poor concentration [3]. To avoid these risks, early diagnosis and treatment are essential [4], [5], and the gold standard for SAS testing is polysomnography (PSG) [6]. PSG records various physiological signals, including electroencephalography (EEG), electrocardiography (ECG), and arterial blood oxygen saturation signals throughout the night using contact-type sensors. When compared with the conventional PSG technique, radar-based noncontact SAS monitoring offers the advantage that the discomfort caused to the patient by contact-type sensors can be avoided, thus enabling monitoring of the SAS signs during natural sleep.

Many existing studies of noncontact detection of sleep apnea (SA) are based on machine learning (ML) methods [7], [8], [9], [10], [11], [12], [13], [14], including long short-term memory (LSTM) [9], [13], [14] and support vector machine (SVM) techniques [8], [10], [11]. Although ML-based methods often require sufficient quantities of training data to be available for accurate classification, it is not easy to collect enough data effectively because the radar data depend on the measurement setup and the surrounding environment and also depend on the positioning and angle of the radar system [9], [13], thus limiting the use of ML in practice.

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In contrast, test methods without the use of ML have also been reported [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], and some of these methods are based on thresholding in terms of the displacement amplitude. For example, in a study by Kagawa et al. [19], [20], a threshold was set up using the amplitude of the displacement caused by normal respiration. Another example is a study by Kang et al. [25] that proposed a method for the use of adaptive thresholding in a constant false alarm rate (CFAR) framework. These methods require prior information about the normal respiration of the target patient, which limits the practicality of the methods.

Unlike conventional ML-based or threshold-based methods, this study introduces a new approach that uses the statistical distribution of respiratory displacement. The proposed method uses the expectation–maximization (EM) algorithm to estimate parameters for stochastic models of respiratory displacement and distinguish between normal breathing and apnea to detect apnea without using numerous training datasets or threshold values. In this study, we conducted experiments on five patients who had been hospitalized for SA testing using PSG and evaluated the accuracy of apnea event detection using the proposed method. Through these experiments, we demonstrate that the proposed method can detect apnea events with higher accuracy than the conventional threshold-based method.

II. SA Detection Using Array Radar

A. Millimeter-Wave Array Radar

In this study, we apply a millimeter-wave radar system that uses the frequency-modulated continuous-wave (FMCW) method with a center frequency of 79 GHz, a center wavelength of $\lambda = 3.8$ mm, range resolution of 43 mm, transmit power of 9 dBm, an equivalent isotropic radiated power of 20 dBm, and a slow-time sampling frequency of 10 Hz. The antennas of this radar system comprise a multiple-input multiple-output (MIMO) array that contains three transmitting elements and four receiving elements, corresponding to a 12-element virtual array; the transmitting and receiving arrays are linear arrays that are equally spaced at intervals of 2λ (7.6 mm) and $\lambda/2$ (1.9 mm), respectively. The radiation pattern for each element is defined as $\pm 4^\circ$ and $\pm 35^\circ$ in the E- and H-planes, respectively. The three transmitting elements radiate signals one-by-one in a time-division multiplexing manner.

B. Radar Imaging and Extraction of Respiratory Displacements

The FMCW radar system transmits a linear chirp signal with a constant amplitude and a frequency $f_{\mathrm{T}}(\tau)$ that increases linearly, as described by $f_{\mathrm{T}}(\tau) = f_0 + B\tau/T_0$ over the interval $0 \le \tau \le T_0$, where τ is a fast time, f_0 is the initial frequency, B is the bandwidth, and T_0 is the chirp duration. The echo reflected from a target located at a distance r from the radar system can be approximated using a time-delayed attenuated copy of the transmitted signal, and the echo frequency $f_{\mathrm{R}}(\tau)$ can thus be expressed as $f_{\mathrm{R}}(\tau) = f_0 + B(\tau - 2r/c)/T_0$, where c is the speed of light. The transmitted and received signals are then input into a mixer with a low-pass filter to generate an intermediate-frequency (IF) signal with a frequency f_{IF}, which is a beat frequency and is given by $f_{\mathrm{IF}} = f_{\mathrm{T}}(\tau) - f_{\mathrm{R}}(\tau) = 2Br/cT_0$. Therefore, to estimate the target range $r = (cT_0/2B)f_{\mathrm{IF}}$, the Fourier transform of the IF signal is calculated to estimate the signal frequency f_{IF}, where the Fourier transform is often implemented using the fast Fourier transform algorithm.

By applying a Fourier transform to the FMCW radar data with regard to the fast time, we obtain a signal $s'_k(t, r)$, where t is the slow time, r is the range, and $k(=0, 1, \ldots, K-1)$ is the element number of the virtual array, with the number of virtual elements being denoted by $K = 12$. Note that the phase of the signal $s'_k(t, r)$ was assumed to be calibrated in advance.

By assuming that the the kth virtual array element is located at $(x, y) = (x_k, 0)$ in the xy plane, where $x_k = k\lambda/2$, the signal vector $\boldsymbol{s}(t, r)$ can then be obtained as follows:

$$\boldsymbol{s}(t, r) = \left[s_0(t, r), s_1(t, r), \ldots, s_{K-1}(t, r)\right]^{\mathrm{T}} \tag{1}$$

where $s_k(t, r) = c_k s'_k(t, r)$, c_k is a Taylor window coefficient and the superscript T denotes a matrix/vector transpose operator. Using the beamformer weight vector $\boldsymbol{w}(\theta) = [w_0, w_1, \ldots, w_{K-1}]^{\mathrm{T}}$ along with $w_k(\theta) = \mathrm{e}^{-\mathrm{j}(2\pi x_k/\lambda)\sin\theta} = \mathrm{e}^{-\mathrm{j}\pi k \sin\theta}$ $(k = 0, 1, \ldots, K-1)$, a complex-valued radar image $I_0(t, r, \theta) = \boldsymbol{w}^{\mathrm{H}}(\theta)\boldsymbol{s}(t, r)$ is then generated, where H denotes the complex conjugate transpose operator.

We then suppress the static clutter components as follows:

$$I_{\mathrm{c}}(t, r, \theta) = I_0(t, r, \theta) - \frac{1}{T_{\mathrm{c}}}\int_{t-T_{\mathrm{c}}}^{t} I_0(\tau, r, \theta)\,\mathrm{d}\tau \tag{2}$$

where $I_{\mathrm{c}}(t, r, \theta)$ is a clutter-free complex-valued radar image and T_{c} is a time period. Because the static clutter components are echoes from nontarget stationary objects, e.g., desks, chairs, and walls, they are not dependent on the slow time t within the time period T_{c}, which means that the static clutter can be estimated by averaging the radar image $I_{\mathrm{c}}(t, r, \theta)$ with respect to t. In this study, we selected the average time length $T_{\mathrm{c}} = 30$ s empirically [26]. We should note here that if the clutter is neither homogeneous nor stationary, other approaches, e.g., circle fitting, must be used to suppress the clutter.

If the signal received contains only a single dominant echo from the target human body, which is located at (r_0, θ_0), then the signal received from an angle θ_0 is approximated to be proportional to the phase-modulated term; i.e., $I_{\mathrm{c}}(t, r, \theta_0) \propto \mathrm{e}^{\mathrm{j}4\pi d_0(t)/\lambda}$ with an echo waveform $p(t, r)$, and the body displacement $d_0(t)$ is thus obtained as follows:

$$d_0(t) = \frac{\lambda}{4\pi}\angle I_{\mathrm{c}}(t, r_0, \theta_0) \tag{3}$$

where $\angle$ represents the phase of a complex number. The respiratory displacement $d(t)$ is estimated using a bandpass filter to suppress the body motion and the random noise components. The cutoff frequencies of the filter are set at 0.17 and 1.8 Hz, corresponding to 0.55 and 6 s in the time domain, respectively.

C. Limitations of the Conventional Apnea Detection Method

According to the American Academy of Sleep Medicine (AASM) scoring criteria for SAS, ventilation is reduced by

30% when compared with normal breathing during hypopnea and by more than 90% during apnea [1], [2], [27], [28], [29], [30], and any such events that last longer than 10 s are counted as hypopnea or apnea, respectively [27], [28]. Therefore, the body motion caused by respiration is reduced during hypopnea and apnea events, and many conventional methods detect this reduced body motion. One such example is the amplitude baseline method (ABM) [19], [20], which is referred to as the conventional method for the purposes of performance comparison in this study.

The displacement amplitude $\bar{d}(t)$ is given by

$$\bar{d}(t) = \sqrt{\frac{1}{T_\mathrm{a}} \int_{t-T_\mathrm{a}/2}^{t+T_\mathrm{a}/2} |d(\tau)|^2 \, \mathrm{d}\tau} \tag{4}$$

where we set $T_\mathrm{a} = 5$ s because the typical respiratory interval is usually shorter than 5 s. The ABM first estimates the body displacement amplitude $\bar{d}_\mathrm{b}$ during normal breathing to act as a baseline and then sets a threshold $\beta \bar{d}_\mathrm{b}$ to detect reduced displacement. Based on consideration of the AASM criteria, the threshold value is set at either 70% or 50% ($\beta = 0.7$ or 0.5) of the amplitude for normal breathing $\bar{d}_\mathrm{b}$. The ABM detects the apnea and hypopnea event period $[t_1, t_2]$, where $\bar{d}(t) < \beta \bar{d}_\mathrm{b}$ holds for any value of t that satisfies the relation $t_1 \le t \le t_2$. In addition, the condition $t_2 - t_1 \ge T_\mathrm{m} = 10$ s must be satisfied according to the AASM criteria.

The limitation of the ABM lies in the fact that normal breathing must first be detected as a baseline, which is not always easy in practice. In addition, the accuracy of the ABM decreases when the patient's position and posture change, which is the reason why a new method is proposed in Section III.

III. Proposed Apnea Detection Method

A. Respiratory Features Extraction With EM Algorithm

We propose a method that uses the EM algorithm for apnea detection. In this method, we regard the respiratory displacement amplitude $\bar{d}$ as a random variable and assume that $\bar{d}$ follows a Gaussian distribution with a mean μ_1 and a variance Σ_1 during apnea and hypopnea events; in addition, we assume that $\bar{d}$ also follows a Gaussian distribution with a mean μ_2 and a variance Σ_2 during normal breathing periods. The respiratory displacement amplitude, including both the apnea and normal breathing, can then be expressed as a Gaussian mixture model.

First, we define the mixing ratios π_1 and π_2 ($\pi_1 + \pi_2 = 1$), which represent the ratios of the time lengths of apnea and normal breathing. Using the vectors $\boldsymbol{\mu} = [\mu_1, \mu_2]^\mathrm{T}$, $\boldsymbol{\Sigma} = [\Sigma_1, \Sigma_2]^\mathrm{T}$, and $\boldsymbol{\pi} = [\pi_1, \pi_2]^\mathrm{T}$, the probability density function $G(\bar{d}|\boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\Sigma})$ of $\bar{d}$ is given by

$$G(\bar{d}|\boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \sum_{k=1}^{K_\mathrm{e}} \pi_k \mathcal{N}(\bar{d}|\mu_k, \Sigma_k) \tag{5}$$

where $\mathcal{N}(\cdot|\mu, \Sigma)$ is the probability density function of a normal distribution with a mean μ and a variance Σ, and the number of mixture components K_e is set to be $K_\mathrm{e} = 2$.

If we assume that $\bar{d}$ is observed M times (i.e., $\bar{d}_i$ ($i = 1, 2, \ldots, M$)), then the log-likelihood function $L(\bar{d}_i|\boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\Sigma})$ is given as follows:

$$\begin{aligned} L(\bar{d}_i|\boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\Sigma}) &= \log \prod_{i=1}^{M} G(\bar{d}_i|\boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\Sigma}) \\ &= \sum_{i=1}^{M} \log \left[\sum_{k=1}^{K_\mathrm{e}} \pi_k \mathcal{N}(\bar{d}_i|\mu_k, \Sigma_k) \right]. \end{aligned} \tag{6}$$

To determine the parameters $\boldsymbol{\mu}$ and $\boldsymbol{\pi}$, we use the EM algorithm, which consists of an expectation (E) step that calculates the posterior probability over the hidden variable $\gamma_{k,i}$ using the current parameters π_k, μ_k, and Σ_k, and a maximization (M) step that estimates the parameters π_k, μ_k, and Σ_k using the current value of $\gamma_{k,i}$. Here, $z_{i,k}$ denotes the probability that the ith data sample $\bar{d}_i$ is generated by the kth Gaussian distribution $\pi_k \mathcal{N}(\bar{d}|\mu_k, \Sigma_k)$. $\gamma_{k,i}$ is estimated as follows:

$$\gamma_{k,i} = \frac{\pi_k \mathcal{N}(\bar{d}_i|\mu_k, \Sigma_k)}{\sum_{k=1}^{K_\mathrm{e}} \pi_k \mathcal{N}(\bar{d}_i|\mu_k, \Sigma_k)}. \tag{7}$$

The optimal parameters π_k^*, μ_k^*, and Σ_k^* are given by

$$\pi_k^* = \frac{M_k}{M} \tag{8}$$

$$\mu_k^* = \frac{1}{M_k} \sum_{i=1}^{M} \gamma_{k,i} \bar{d}_i \tag{9}$$

$$\Sigma_k^* = \frac{1}{M_k} \sum_{i=1}^{M} \gamma_{k,i} \left(\bar{d}_i - \mu_k^*\right)^2 \tag{10}$$

where $M_k = \sum_{i=1}^{M} \gamma_{k,i}$.

B. Proposed Apnea Detection Method

We propose a radar-based system for apnea detection, as illustrated in Fig. 1. The proposed system consists of a radar signal processing block and an SA detection block.

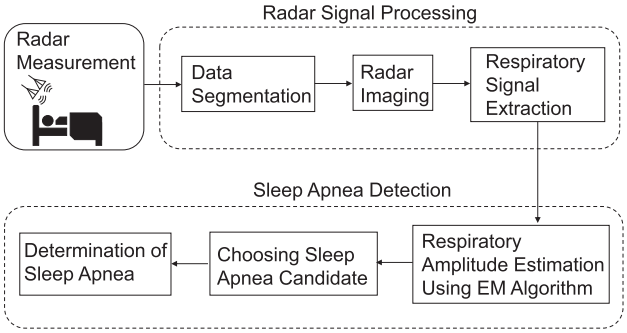

Fig. 1. Overview of the proposed apnea detection method.

First, the overnight radar signal data are divided into epochs, with each having a period of $T_\mathrm{ep} = 60$ s, where the adjacent epochs overlap by 30 s following the convention of the PSG test procedures. Next, the radar image $I_\mathrm{p}(r, \theta)$ is generated as follows:

$$I_\mathrm{p}(r, \theta) = \frac{1}{T_\mathrm{ep}} \int_0^{T_\mathrm{ep}} |I_\mathrm{c}(t, r, \theta)|^2 \, \mathrm{d}t. \tag{11}$$

From the radar image $I_\mathrm{p}(r, \theta)$, local maxima with intensities greater than a specific threshold are extracted, and their range

and azimuth characteristics are obtained from (r_m, θ_m) $(m = 1, 2, \ldots, M)$, which correspond to multiple scattering centers on the human body. From the results for the positions (r_m, θ_m), we obtain a respiratory displacement $d_m(t)$ and an amplitude $\bar{d}_m(t)$ using (3) and (4). The proposed method uses the displacement waveform not only at a single scattering center but also at multiple scattering centers across the human body because the apnea and hypopnea movements vary depending on the body part involved [28]. By applying the EM algorithm to the displacement amplitude $\bar{d}_m(t)$, the parameters $\pi_{k,m}$, $\mu_{k,m}$, and $\Sigma_{k,m}$ $(k = 1, 2)$ are estimated, where $\mu_{1,m} \leq \mu_{2,m}$.

Let us define a label $l_m(t)$ as $l_m(t) = 1$ if an apnea and hypopnea event is detected from the mth displacement amplitude at a time t, and let $l_m(t) = 0$ otherwise. The proposed method estimates this label as follows:

$$l_m(t) = \begin{cases} 1, & \text{if } \gamma_{1,m}(t) \leq \gamma_{2,m}(t), \text{ and } \dfrac{\mu_{1,m}}{\mu_{2,m}} \leq \beta \\ 0, & \text{otherwise.} \end{cases} \tag{12}$$

Here, we set $\beta = 0.5$ based on the AASM scoring criteria that were established in 1999 [2], [27], [28]. In (12), the presence or absence of apnea and hypopnea events is determined by the ratio of $\mu_{1,m}$ to $\mu_{2,m}$. Finally, we make our decision by using all $l_m(t)$ $(m = 1, \ldots, M)$ as shown

$$l(t) = \begin{cases} 1, & \text{if } \displaystyle\sum_{m=1}^{M} l_m(t)\mu_{2,m} > \sum_{m=1}^{M} \mu_{2,m}/2 \\ 0, & \text{otherwise.} \end{cases} \tag{13}$$

This approach detects the presence of an apnea and hypopnea event if that apnea and hypopnea event is detected at the majority of the patient's body parts in the radar signals. Because each epoch has a 50% overlap with its neighboring epoch, the sum of the labels $l(t)$ for each of the apnea events must be either 0, 1, or 2. Therefore, the proposed method only detects the presence of an apnea and hypopnea event when this sum value reaches 2 and the event lasts for more than 10 s.

IV. Experimental Performance Evaluation

A. Overview of the Experimental Setup

To evaluate the performance of the proposed method, we performed radar measurements on patients with SAS symptoms, where the radar and PSG measurements were performed simultaneously, and an evaluation was also performed using conventional medical diagnostic results. The details of the five participating patients with minor to moderate SAS symptoms are presented in Table I. Fig. 2 shows the measurement setup with the radar system in a hospital room. Because we are interested in apnea and hypopnea events in this work, we only analyzed the radar data acquired when the patients were asleep. The awakeness of each patient was detected using the PSG data. In Section IV-B, we apply the proposed method to the radar data and compare the results with the PSG data to evaluate the method's performance.

B. Application of the Proposed Method

In this section, we apply the proposed method to the experimental data to evaluate the method's performance. Fig. 3 shows a radar image $I_p(r, \theta)$ that was obtained from data acquired while the patient was asleep, in which we see a set of strong echoes at a range of approximately 1.5 m; this suggests that these echoes arrive from not a single point on the target person's body, but from multiple points. The body displacement waveforms measured at these multiple points were then used to detect apnea and hypopnea events when using the proposed method.

Figs. 4 and 5 show examples of the respiratory displacements measured using the radar system during normal breathing and during apnea and hypopnea events, respectively. In Fig. 4(a)–(d), the respiratory amplitudes remained almost constant within the 60-s epoch. In contrast, in Fig. 5, the apnea and hypopnea respiratory amplitudes were reduced (red lines) when compared with normal respiration (black lines). Fig. 5(a) and (d) shows the obstructive SA (OSA) signs and (b) shows the hypopnea sign. In these three panels, respiratory efforts, i.e., periodic movements similar to those of normal breathing when the amplitude is decreasing, were found. However,

Fig. 2. Measurement setup with millimeter-wave array radar system in a hospital room.

TABLE I
PATIENT DETAILS

Patient number	Radar measurement time (h)	Number of apnea events
1	7.0	104
2	6.5	154
3	5.5	68
4	7.0	25
5	8.0	117

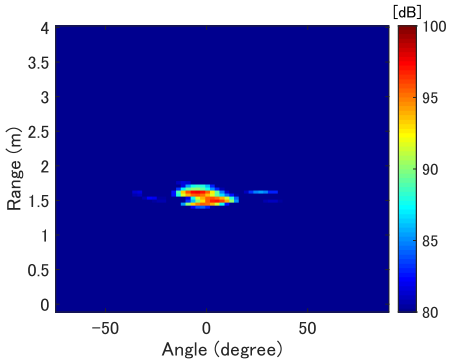

Fig. 3. Example of the radar image $I_p(r, \theta)$.

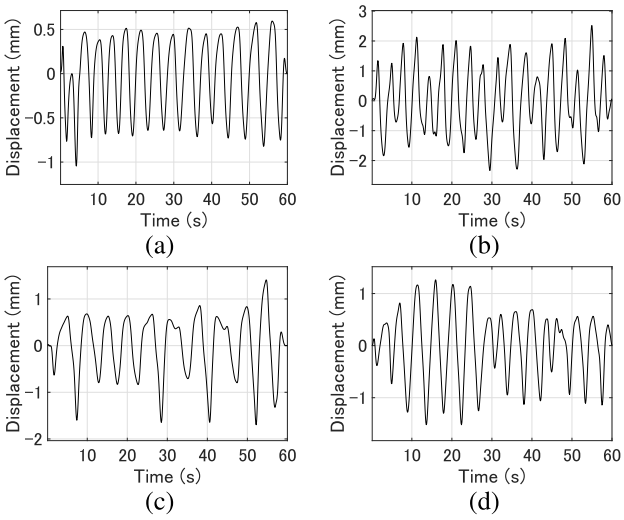

Fig. 4. Examples of respiratory displacements observed during normal breathing. (a) Participant 1, (b) participant 3, (c) participant 4, and (d) participant 5.

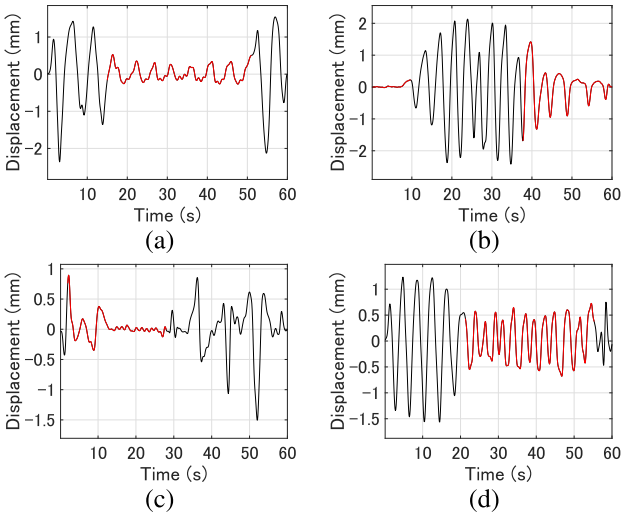

Fig. 5. Examples of respiratory displacements observed when apnea and hypopnea events occur. (a) Participant 1, (b) participant 3, (c) participant 4, and (d) participant 5.

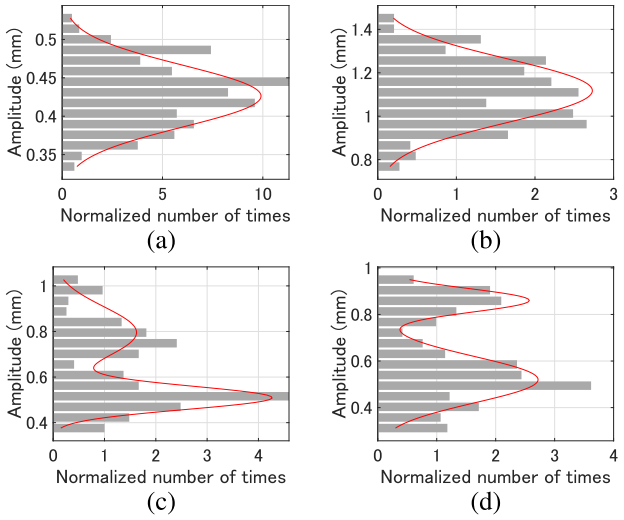

Fig. 6. Probability density functions estimated using the EM algorithm for respiratory amplitudes during normal breathing. (a) Participant 1, (b) participant 3, (c) participant 4, and (d) participant 5.

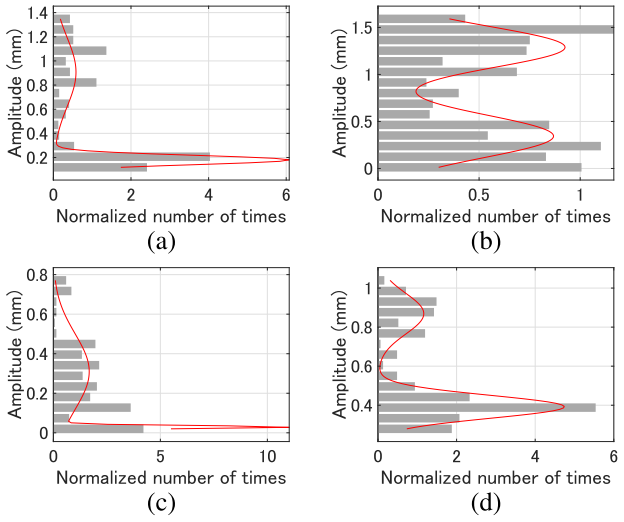

Fig. 7. Probability density functions estimated using the EM algorithm for respiratory amplitudes when apnea and hypopnea events occur. (a) Participant 1, (b) participant 3, (c) participant 4, and (d) participant 5.

no respiratory effort was observed in Fig. 5(c), showing the central SA (CSA) sign. Therefore, apnea and hypopnea events can be determined visually to some extent from the respiratory displacements measured using radar. We note that all participants' apnea and hypopnea may have included central apnea and hypopnea, nonetheless, most SAS patients have OSA symptoms, and the detection of OSA events is considered important.

Fig. 6 shows examples of the histograms of the respiratory amplitudes (gray bars) and the corresponding probability density functions of the mixed Gaussian distributions that were estimated using the EM algorithm, where each panel (a)–(d) corresponds to (a)–(d) in Fig. 4. In Fig. 6(a) and (b), only one peak is observed, whereas in Fig. 6(c) and (d), we can see two peaks that approximately correspond to μ_1 and μ_2 ($\mu_1 < \mu_2$). This illustrates that there can be two peaks in these characteristics, even when the breathing is normal.

Fig. 7 also shows example histograms of the respiratory amplitudes (gray bars) and the corresponding probability density functions when the apnea and hypopnea events occur, corresponding to Fig. 6. In this case, we can see two peaks in all panels and the peak gaps are larger than those observed in Fig. 6 (i.e., μ_1/μ_2 is larger). The proposed method uses these characteristics to detect the apnea and hypopnea events automatically.

C. Accuracy Evaluation of the Proposed Method

This section provides a performance evaluation of the proposed method by comparing it with the conventional ABM. For this performance evaluation, we use the apnea–hypopnea index (AHI), which represents the combined number of apneas and hypopneas that occur per hour during sleep and is used to diagnose the severity of a patient's SAS. In addition, we also evaluate the accuracy of estimation of the number of apnea

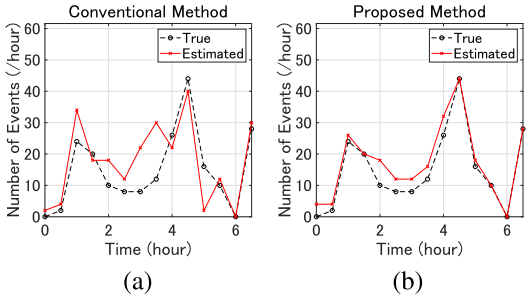

Fig. 8. Number of apnea and hypopnea events estimated at 30-min intervals for participant 1 when using (a) conventional and (b) proposed methods.

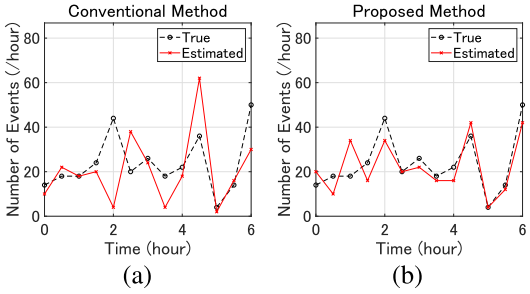

Fig. 9. Number of apnea and hypopnea events estimated at 30-min intervals for participant 2 when using (a) conventional and (b) proposed methods.

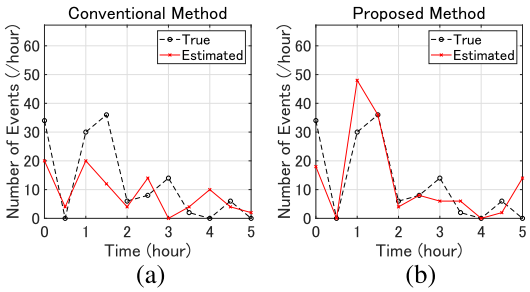

Fig. 10. Number of apnea and hypopnea events estimated at 30-min intervals for participant 3 when using (a) conventional and (b) proposed methods.

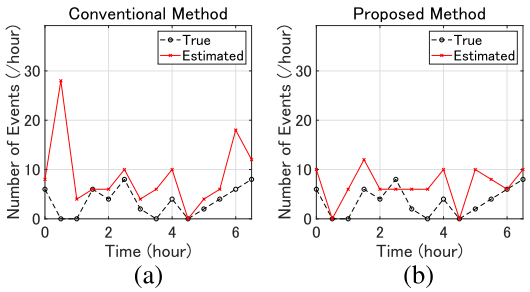

Fig. 11. Number of apnea and hypopnea events estimated at 30-min intervals for participant 4 using (a) conventional and (b) proposed methods.

and hypopnea events per 30 min, which we then convert into the number per hour by simply doubling the number.

Figs. 8–12 show the numbers of apnea and hypopnea events per hour for each participant. In each figure, the red lines in (a) and (b) indicate the estimates from the conventional and proposed methods, respectively. The true numbers of apnea and hypopnea events, which are plotted as black dashed lines, were obtained from the PSG data and the doctor's diagnosis.

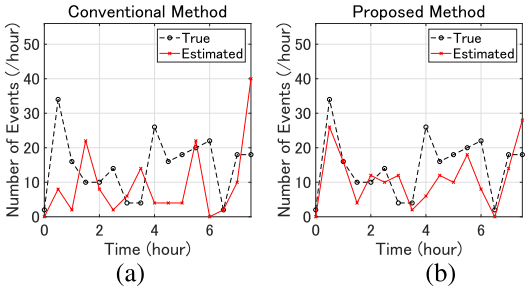

Fig. 12. Number of apnea and hypopnea events estimated at 30-min intervals for participant 5 using (a) conventional and (b) proposed methods.

TABLE II
RMS ERRORS OF ESTIMATED NUMBERS OF APNEA AND HYPOPNEA EVENTS PER HOUR

Patient number	Conventional method	Proposed method
1	8.2	3.5
2	15.9	7.2
3	10.6	8.9
4	8.7	4.4
5	14.0	7.9
Mean	11.5	6.4

TABLE III
AHI ESTIMATED USING THE CONVENTIONAL AND PROPOSED METHODS (TIMES/HOURS)

Patient		Conventional method		Proposed method	
No.	AHI	Estimated AHI	Error	Estimated AHI	Error
1	30.4	35.9	5.5	35.6	5.2
2	51.1	44.5	6.6	47.8	3.3
3	27.2	18.8	8.4	28.4	1.2
4	7.4	18.2	10.8	14.2	6.8
5	30.3	19.1	11.2	23.0	7.3
Mean	-	-	8.5	-	4.8

Table II shows the root-mean-square (rms) errors calculated for the estimated numbers of apnea and hypopnea events as shown in Figs. 8–12. For all patients, the rms error of the proposed method was shown to be smaller than that of the conventional method. The rms error averaged over all patients was 11.5 times/h when using the conventional method, whereas the corresponding value when using the proposed method was 6.4 times/h, representing an improvement in accuracy of 1.8 times.

Table III summarizes the AHI values that were estimated using both the conventional and proposed methods. The AHI was estimated to have an average error of 8.5 times/h when using the conventional method and 4.8 times/h when using the proposed method, again resulting in an improvement of 1.8 times. Because the diagnostic criterion for SA is AHI $\geq$ 5 times/h, the proposed method estimates the AHI with an accuracy of 4.8 times/h, which reaches the minimum accuracy requirement for diagnosis. These results illustrate the effectiveness of the proposed method for the detection of apnea and hypopnea events in a noncontact manner using a radar system.

V. Discussion

In this study, we have proposed a method for the detection of SA/hypopnea events that can be regarded as decision problems for two hypotheses (i.e., normal breathing and apnea/hypopnea). In decision theory, statistical approaches such as the generalized likelihood ratio test are available. However, rather than adopt an existing statistical method, we have developed a new approach because it is difficult to identify the appropriate statistical model for the radar-measured body displacements caused by respiration that includes apnea and hypopnea, partly because insufficient quantities of radar-measured respiratory displacement data have been collected from patients. In fact, the amplitudes and waveforms of radar-measured respiratory displacement signals are affected strongly by individual differences, and they are also dependent on the type of apnea/hypopnea [i.e., OSA, CSA, and mixed SA (MSA)], the body part to be measured (e.g., the chest, abdomen, front, or back), and the patient's posture (supine, prone, and lateral recumbent positions).

In our problem setting, the EM-based procedure represents the first choice because the EM algorithm is the most commonly used unsupervised approach for the estimation of the model parameters in cases where the statistical distribution is expressed using a Gaussian mixture model. In addition, the use of the EM algorithm allows us to obtain the ratio of the respiratory amplitude for normal breathing to the respiratory amplitude for apnea/hypopnea; this ratio can then be used to detect reduced ventilation due to apnea/hypopnea directly based on the AASM criteria. For these reasons, we selected the EM-based approach rather than use other decision statistics methods for the detection of SA/hypopnea. Despite this, it will be important to investigate the possibility of the application of other statistics-based methods to determine the decision boundary to improve the detection accuracy; however, this aspect will form part of our future studies.

One of the drawbacks of our proposed method is that it is unable to distinguish unwanted limb movements from physiological body displacements, and it is thus suspected that our approach is affected negatively by patient body motion, which can reduce the detection accuracy. Therefore, it will be important to extend our method by including a technique to detect these limb movements and improve the overall detection accuracy in future work. Another important step will be integration of the proposed radar-based method with the PSG system, which has been studied intensively in the literature [31], [32], [33], [34].

VI. Conclusion

In this study, we have proposed a novel method for noncontact radar-based SA detection. The proposed method achieves adaptive apnea detection without prior knowledge of the respiratory amplitude of normal breathing. The proposed method uses a histogram of the respiratory amplitude as measured using a radar system, and then detects single or double peaks using the EM algorithm to distinguish the apnea and hypopnea events from normal breathing. To evaluate the performance of our proposed method, we performed experiments using both radar and PSG systems on five patients with SA symptoms. The experimental results showed that the proposed method estimated the AHI with an accuracy that was 1.8 times higher than that of the conventional method, confirming the effectiveness of the proposed method. In addition, we also demonstrated that the proposed method was able to estimate the AHI with a mean error of only 4.8 times/h, which met the minimum accuracy requirement for use in SAS diagnosis. In conclusion, the proposed method was shown to be effective in using radar to perform noncontact apnea detection.

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