Polyvinylidene fluoride sensor-based method for unconstrained snoring detection

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Polyvinylidene fluoride sensor-based method for unconstrained snoring detection

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Abstract

We established and tested a snoring detection method using a polyvinylidene fluoride (PVDF) sensor for accurate, fast, and motion-artifact-robust monitoring of snoring events during sleep. Twenty patients with obstructive sleep apnea participated in this study. The PVDF sensor was located between a mattress cover and mattress, and the patients’ snoring signals were unconstrainedly measured with the sensor during polysomnography. The power ratio and peak frequency from the short-time Fourier transform were used to extract spectral features from the PVDF data. A support vector machine was applied to the spectral features to classify the data into either the snore or non-snore class. The performance of the method was assessed using manual labelling by three human observers as a reference. For event-by-event snoring detection, PVDF data that contained ‘snoring’ (SN), ‘snoring with movement’ (SM), and ‘normal breathing’ epochs were selected for each subject. As a result, the overall sensitivity and the positive predictive values were 94.6% and 97.5%, respectively, and there was no significant difference between the SN and SM results. The proposed method can be applied in both residential and ambulatory snoring monitoring systems.

Keywords: snoring, PVDF sensor, unconstrained monitoring of snoring, sleep-related breathing disorder

(Some figures may appear in colour only in the online journal)
1. Introduction

Snoring is a typical sleep-related breathing disorder (SRBD) characterized by loud, noisy respiratory sounds during sleep, caused by the vibration of the soft palate and the uvula (American Academy of Sleep Medicine 2005). Snoring is common in the general population, and the prevalence of snoring varies widely among studies: 24–86% of men and 14–57% of women (Lugaresi et al 1980, Norton et al 1983, Dalmasso and Prota 1996, Scott et al 2003). Some previous studies have shown that snoring is associated with excessive daytime sleepiness (Gottlieb et al 2000), and hypertension (Lugaresi 1975, Bixler et al 2000); however, it is difficult to ascertain how many of these health risks are attributable to snoring alone (Kryger et al 2011).

Nonetheless, snoring detection has clinical significance because snoring may indicate undiagnosed obstructive sleep apnea (OSA) (Hoffstein et al 1996). Apnea-induced hypoxia during sleep can also lead to severe cardiovascular disease (Peker et al 1997, Bhattacharjee et al 2009). Additionally, severe and frequent snoring can disrupt the spouse’s sleep (Norton et al 1983).

Conventionally, polysomnography (PSG) has been the preferred method used in sleep and SRBD assessment systems. According to the manual issued by the American Academy of Sleep Medicine (AASM) for scoring sleep and associated events, an acoustic sensor (such as a microphone), piezoelectric sensor, or nasal pressure transducer are recommended for snoring monitoring during PSG (Iber and AASM 2012). Although PSG has been used for the assessment of SRBD, the detection of snoring using PSG has several limitations. PSG recording can interrupt comfortable sleep because numerous sensors are attached to the face and body of the sleeper. Furthermore, some PSG reports do not provide objective information about snoring (number of occurrences, duration, etc.) because snoring recording during PSG is optional (Iber and AASM 2012) and is used to assess only the existence of snores rather than the details of snoring occurrences.

To overcome these PSG problems, other previous studies have proposed acoustic snoring evaluation methods without PSG. Most of these methods implement one or more microphones placed on the trachea or a location close to the sleeper’s bed (freestanding, near the mouth, or over the head) (Duckitt et al 2006, Cavusoglu et al 2007, Yadollahi and Moussavi 2010, Azarbarzin and Moussavi 2011, Emoto et al 2012). Although snoring events were detected successfully by these methods (sensitivity ranging from 82.2% to 94.8%), these microphone-based methods can be affected by ambient noise and their performance can vary depending on the position of the microphone (Pevernagie et al 2010). Furthermore, microphone-based methods require a high sampling rate of over 10kHz to analyse the acoustic characteristics of the snoring sounds, and the high processing cost of the necessary microcontroller may render these methods unsuitable for residential or ambulatory monitoring devices.

Alternative snoring detection methods without using microphones have also been investigated. Shin et al evaluated the performance of noninvasively monitoring the events of snoring using an air mattress with a balancing tube system (Shin et al 2010, Lim et al 2011). Although the system unconstrainedly measured a subject’s snoring signals, a detection process was not applied on data acquired during real nocturnal sleep. Lee et al proposed a snoring detection method based on a piezoelectric snoring sensor that measured the vibration related to snoring (Lee et al 2013). However, this piezoelectric snoring sensor was attached to the neck during PSG recording, and the attachment of the sensor could interrupt comfortable sleep.

Polyvinylidene fluoride (PVDF) is a very thin and flexible film that has piezoelectric properties. PVDF was used in previous studies as a sensor for recording several physiological signals such as respiration (Siivola 1989, Choi and Jiang 2006, Roopa Manjunatha et al 2013),
heart rate (Wang et al. 2003), and ballistocardiogram (BCG) (Baek et al. 2012, Chiu et al. 2013). Although using PVDF as a physiological sensor has the advantage of unconstrained measurement, the effect of motion artifacts was not considered in the studies mentioned above. Motion artifacts are important because PVDF is very sensitive to minute movements and vibrations (Choi and Jiang 2006, Baek et al. 2012). Recently, a PVDF film-based contactless monitoring system (Sonomat) was evaluated for the diagnosis of SRBD (Norman et al. 2014). Sonomat appeared to be a reliable device for the detection of OSA events and snoring times. Although this concept of a sensor was similar to our system, events recorded by Sonomat were manually scored by PSG scorers, and an automated snoring detection method was not suggested in that study. Moreover, analysis of event-by-event snoring detection was not conducted for comparison between the Sonomat system and PSG.

In our previous study, we developed a sleep apnea monitoring method using a PVDF sensor (Hwang et al. 2014). In that study, we could estimate the severity of sleep apnea, and our results were highly correlated with those of PSG ($R = 0.94$). If we can also develop a snoring monitoring method using a PVDF sensor, we will be able to monitor the two main symptoms of SRBD in an unconstrained manner.

Therefore, this study was conducted to establish an unconstrained snoring monitoring method using a PVDF sensor with high accuracy, low computational cost, and robustness with regard to motion artifacts.

2. Methods

2.1. Participants and PSG data

Twenty subjects with OSA participated in this study, and overnight PSGs were conducted at Seoul National University Hospital (SNUH). On the basis of the standard PSG routine (Iber and AASM 2012), data were collected from an electroencephalogram (EEG); bilateral electrooculogram (EOG); electromyogram (EMG) from the mandible and bilateral tibialis anterior muscles, nasal-ororal airflow, abdominal and thoracic movement; lead II electrocardiogram (ECG); pulse oximetry (SpO2); body position; and a reference snoring signal from a piezoelectric vibration sensor (Cadwell, Kennewick, WA, USA) placed on the neck. Snoring signals from the PVDF sensor were simultaneously recorded with the PSG data. All of the signals were collected using a NI-DAQ 6221 (National Instruments, Austin, TX, USA) device with a 250 Hz sampling frequency. After PSG recording, sleep stages and associated events including sleep apnea were scored by a registered polysomnographic technologist according to the established criteria (Iber and AASM 2012).

The Institutional Review Board of SNUH approved all of these procedures, and all of the subjects were provided with information about the methods and purpose of the study. Table 1 summarizes the parameters related to the subjects and PSG results.

2.2. Snoring signal acquisition system

The snoring signals of the subjects were measured using the PVDF sensor. During snoring occurrences, the vibration of respiratory structures caused by the obstructed air movement was detected by the PVDF sensor, and the output signals of the sensor reflected the snoring of the subjects. The sensor was composed of a $4 \times 1$ array positioned under the subject’s back. It was installed between a mattress cover and the mattress to avoid direct contact with the subject’s body. The shape and size of the sensor, and a conceptual diagram of the system installation, are shown in figure 1. The total thickness of the sensor and its protective silicon
The sensor was a 122 μm-thick silver ink metalized piezoelectric film sensor (part number: 3-1004-346-0, Measurement Specialties, Inc., Hampton, VA, USA), and the cost of a single sheet (8 × 11 in) of the sensor was approximately $300. PVDF data were collected from July 2012 to October 2013, and the sensor’s durability over more than one year was verified. During the experiments, sweat did not affect signal quality because the PVDF sensor’s functionality is mainly based on its piezoelectric properties. After PSG recording, none of the subjects reported an uncomfortable feeling, and all responded that the sensor did not interfere with their sleep. Because the subjects did not experience physical or mental stress, we can conclude that the proposed sensor is appropriate for unconstrained snoring monitoring.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Mean ± SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender (male/female)</td>
<td>17/3</td>
</tr>
<tr>
<td>OSA severity (mild/moderate/severe)</td>
<td>1/7/12</td>
</tr>
<tr>
<td>AHI (events/h)</td>
<td>41.8 ± 19.3</td>
</tr>
<tr>
<td>Age (years)</td>
<td>49.4 ± 13.6</td>
</tr>
<tr>
<td>BMI (kg/m²)</td>
<td>28.2 ± 3.7</td>
</tr>
<tr>
<td>Sleep latency (min)</td>
<td>6.2 ± 4.0</td>
</tr>
<tr>
<td>Stage N1 &amp; N2 (%)</td>
<td>63.7 ± 9.9</td>
</tr>
<tr>
<td>Stage N3 (%)</td>
<td>4.5 ± 7.0</td>
</tr>
<tr>
<td>Stage REM (%)</td>
<td>16.7 ± 4.9</td>
</tr>
<tr>
<td>Total sleep time (h)</td>
<td>8.1 ± 0.5</td>
</tr>
<tr>
<td>Sleep efficiency (%)</td>
<td>86.1 ± 8.0</td>
</tr>
</tbody>
</table>

SD, standard deviation; AHI, apnea hypopnea index; BMI, body mass index; REM, rapid eye movement; N, non-REM sleep.

**Figure 1.** Conceptual diagram of system size and installation.
2.3. Feature extraction for snoring event detection

As shown in figure 2, the signal outputs of the PVDF sensor include many types of physiological signals, including respiration, ballistocardiogram (BCG), and snoring. When snoring occurred, the sensor signal was relatively noisy and had no standard waveform compared to the other bio-signals. Thus, this study used spectral features to distinguish snoring events from normal breathing, body movement, or other physiological signals.

The unprocessed data from four channels were averaged and band-pass filtered with a pass-band of 10 to 100 Hz, which is the recommended filter band for snoring recordings from the AASM manual (Iber and AASM 2012). The data were also notch filtered at 60 Hz to remove power line noise. After filtering, two spectral features were extracted using a short-time Fourier transform (STFT). The STFT is expressed as follows:

\[
X[n, k] = \sum_{m=0}^{L-1} x[n + m] w[m] e^{-j2\pi km/N}
\]

where \( n \) is the sample number, \( x[n] \) is the filtered PVDF data, \( w[m] \) is the 128-point sliding Kaiser window function, \( k \) is the frequency index, and \( L \) is the length of the analysis window. The STFT analysis was conducted using a 256-fast Fourier transform (FFT) length with 10 overlapping samples. The type and length of the sliding window, FFT length, and overlapping samples were set experimentally. As shown in figures 3(a) and (b), when snoring occurred, the PVDF spectrum included significant frequency components and peak frequency of over 25 Hz, whereas these frequency characteristics did not occur during movement or breathing, as shown in figures 3(c) and (d).

Figure 2. Sample of the signal output from the PVDF sensor for several physiological signals.
Additionally, previous literature reported that PVDF signals containing periodic components with fundamental peak frequency from 20–30 Hz to approximately 250–300 Hz were manually scored as snore events (Norman et al 2014). With these criteria, we selected the following two spectral features to detect snoring events. The first spectral feature was the power ratio (PR), which is the ratio of the sum of power produced at greater than 25 Hz to the sum of power produced at less than 25 Hz.

\[
PR_n = \frac{\sum_{k=27}^{N-1} X[n,k]}{\sum_{k=0}^{26} X[n,k]} \quad (2)
\]

The other feature was peak frequency (PF), which is the maximum value among the frequency (\(k\)) values in each fixed time (\(n\)), as described by (3).

\[
PF_n = k_{\text{max}}, \quad \text{where} \quad |X[n,k_{\text{max}}]| = \max |X[n,k]| \quad (3)
\]

Examples of the PR and PF are shown in figure 4. As shown in the figure, there were no significant changes in either PR or PF when body movement occurred, whereas both increased during snoring. After feature extraction, PR and PF were used as the input to the support vector machine (SVM) for classification. In this study, we used only these two spectral features to establish a fast and simple snoring detection algorithm.
2.4. Data selection and reference snoring labelling

To establish the snoring detection algorithm, 50 epochs of PVDF data composed of 20 ‘snoring’ (SN), 20 ‘snoring with movement’ (SM), and 10 ‘normal breathing’ (NB) epochs were randomly selected for each subject (totalling 1000 epochs of data). The descriptions of the SN, SM, and NB epochs are:

- SN: only snoring occurred in an unmoving state.
- SM: both snoring and body movement occurred.
- NB: normal breathing without snoring.

In this study, the EMG signal from the tibialis anterior muscle was applied as a reference for assessing body movement. If the output voltage of the EMG signal exceeded 4.5 V (almost saturated), the signal was scored as body movement.

Because there is no clear definition for a ‘snoring event,’ reference snoring events were visually and aurally observed by three healthy human observers without any recognised auditory impairments. First, each observer saw only the reference snoring signal waveform from the PSG snoring sensor on an LCD monitor (SyncMaster T240HD, Samsung, Korea) to confirm the snoring events. A consensus was reached if each observer’s labelling concurred within 1 s of each other, and the labelling results from all of the observers were combined into a single label by applying a logical AND operation. In other words, the overall event result became a non-snore if at least one the observers scored the data as a non-snore. For events on which the observers did not concur, the observers reconfirmed the events by listening to the converted
audio files using headphones (EH-150, Sennheiser, Germany). The results of each observer’s labelling process were not revealed to the other observers.

2.5. Snoring event classification based on the SVM

The SVM is a supervised machine learning model used for classification or regression analysis. The SVM constructs a maximum-margin hyperplane between the two classes, and the support vectors indicate the feature points that are closest to the hyperplane (Cortes and Vapnik 1995). An equation of the separating hyperplane for binary classification can be described as

\[
d(x) = w \cdot x + b, \quad \text{class}(z) = \text{sign}(d(z))
\]

where \(x\) is the feature vector, \(w\) is the normal vector to the hyperplane, \(\cdot\) denotes the dot product, and \(b\) is the bias. Through the machine learning process, the margin-maximizing values of \(w\) and \(b\) are obtained. The SVM can be effectively applied to nonlinear classification by mapping the feature data into higher dimensions, where it exhibits linear patterns, which is called the ‘kernel trick’ (Aizerman et al 1964). Therefore, the selection of the proper kernel function is critical because classification performance can vary for the same data. To generalize and simplify the algorithm, a linear kernel function of the SVM was used in this study. Figure 5 shows the distribution of the sample data in the feature space before and after transformation using the linear kernel function. As shown in figure 5(b), snore classes were separated from the other classes by the hyperplane of the SVM in the transformed space.

**Figure 5.** Scatter plot of three categorized classes in the feature space (a) before transformation, and (b) after transformation using the linear kernel function.
Using the SVM classification, each result was first classified into two categories: 'snore' or 'non-snore.' In this study, non-snore events included all but the snore events, including normal breathing, body movement, and silence. Finally, two post-processing steps were conducted to prevent overestimation of the snore events. First, a snore event decision was made if there were two or more consecutive snore events. Second, if two distinct snore events occurred within 1 s, they were considered together as a single snoring event. All snoring detection procedures are shown schematically in figure 6.

3. Results

3.1. Event-by-event snoring detection

For the validation of the algorithm, the SVM was trained and tested on the basis of the leave-one-out cross-validation (LOOCV) technique. In other words, 950 epochs of data from 19 subjects were used as a training set for the SVM and 50 epochs (20 SN, 20 SM, and 10 NB) of data from one subject were selected as a test set, and this procedure was repeated 20 times for each subject. After applying LOOCV, the snoring event detection results were compared with those from the reference snoring labelling. To evaluate the performance of our algorithm, sensitivity and positive predictive value (PPV) were used. Sensitivity is defined as TP/(TP + FN) and PPV is defined as TP/(TP + FP), where TP, FN, and FP denote true positive, false negative, and false positive, respectively. In our study, TP represents the number of events correctly classified as snore events. Table 2 shows the SN, SM, and NB classification results.
for all 1000 epochs. From the Mann–Whitney–Wilcoxon test, there were no significant differences in the sensitivity ($p = 0.461$) and PPV ($p = 0.072$) values between the SN and SM results from our method and those from the reference labelling.

Examples of snore event detection for the SN, SM, and NB epochs are shown in figure 7. As shown in figure 7(b), snore-related PVDF data were correctly classified as snore events whereas body movement events were correctly classified as non-snore events.

Table 3 shows a comparison between the snore event detection results from the proposed method and those from previous studies. The snore event detection sensitivity from the ambient microphone-based methods had lower performance (1.5–12.4%) compared with ours (Duckitt et al 2006, Cavusoglu et al 2007, Azarbarzin and Moussavi 2011, Emoto et al 2012), except for one case (Yadollahi and Moussavi 2010). In other studies, air mattress- (Shin et al 2010) and piezo snoring sensor-based (Lee et al 2013) methods showed a slightly lower sensitivity than our method.

### 3.2. Snoring event detection and sleep posture

Snoring detection performance was also evaluated by sleep posture. During PSG, the sleep posture of each subject was obtained using a sleep position sensor (SPL Lite, Pro-Tech, USA). The sleep position sensor provided four categories of posture (supine, prone, right lateral, and left lateral). After SVM classification, snoring detection results were classified according to the sleep posture, as shown in table 4. A Kruskal–Wallis one-way analysis of variance (ANOVA) test (Kruskal and Wallis 1952) was then used to assess the difference in results.
between different postures; there were no significant differences in the sensitivity ($p = 0.194$) and PPV ($p = 0.649$) values.

### 3.3. Epoch-by-epoch snoring detection

Snoring detection performance was also evaluated using one entire night of PVDF data. Overnight data from 10 randomly selected participants (out of 20 total participants) were subjected to epoch-by-epoch analysis. For the analysis, if snoring events occurred more than once in one epoch of PVDF data, that epoch was considered to be an ‘estimated snore epoch.’ The same rule was applied to reference snore signals, and epoch-by-epoch statistical analysis between the ‘estimated snore epoch’ and a ‘reference snore epoch’ was performed. The epoch-by-epoch results are shown in table 5. A kappa statistical analysis revealed a borderline case between almost perfect ($0.8 < k < 1$) and substantial agreement ($0.6 < k < 0.8$), whereby the overall $k = 0.8$ (Landis and Koch 1977).

Figure 8 shows the snore epoch estimation results for the best case (figure 8(a), subject #2) and the worst case (figure 8(b), subject #1). In the best case, the sensitivity, specificity, accuracy, and kappa statistic were 98.3%, 86.0%, 94.9%, and 0.87, respectively. In the worst case, the corresponding values were 95.9%, 75.8%, 87.6%, and 0.74, respectively.

---

### Table 3. Comparison with previous studies.

<table>
<thead>
<tr>
<th>Author (year)</th>
<th>Sensor</th>
<th>Class</th>
<th>N</th>
<th>Labelling</th>
<th>Sensitivity (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Duckitt (2006)</td>
<td>Mic</td>
<td>Snore/ others</td>
<td>6 snores</td>
<td>Manually</td>
<td>82.2</td>
</tr>
<tr>
<td>Cavusoglu (2007)</td>
<td>Mic</td>
<td>Snore/ non-snore</td>
<td>18 snores, 12 OSA</td>
<td>ENT specialist</td>
<td>90.2</td>
</tr>
<tr>
<td>Yadollahi (2010)</td>
<td>Mic (ambient)</td>
<td>Snore/ breathing</td>
<td>23 OSA</td>
<td>Auditory &amp; visual</td>
<td>94.8</td>
</tr>
<tr>
<td>Mic (tracheal)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>98.3</td>
</tr>
<tr>
<td>Shin (2010)</td>
<td>Air mattress</td>
<td>Snore/ breathing</td>
<td>6 normal</td>
<td>Simulation</td>
<td>93.0</td>
</tr>
<tr>
<td>Azarbarzin (2011)</td>
<td>Mic (ambient)</td>
<td>Snore/ non-snore</td>
<td>7 snores, 23 OSA</td>
<td>Auditory &amp; visual</td>
<td>93.1</td>
</tr>
<tr>
<td>Mic (tracheal)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>98.6</td>
</tr>
<tr>
<td>Emoto (2012)</td>
<td>2 Mic</td>
<td>Snore/ breathing</td>
<td>4 normal, 4 OSA</td>
<td>Listening</td>
<td>89.2</td>
</tr>
<tr>
<td>Lee (2013)</td>
<td>Piezo snoring</td>
<td>Snore/ silence</td>
<td>21 OSA</td>
<td>Technician</td>
<td>93.3</td>
</tr>
<tr>
<td>Hwang</td>
<td>PVDF</td>
<td>Snore/ non-snore</td>
<td>20 OSA</td>
<td>Auditory &amp; visual</td>
<td>94.6</td>
</tr>
</tbody>
</table>

OSA, obstructive sleep apnea; ENT, ear-nose-throat, Mic, microphone.

### Table 4. Snoring detection performance based on sleep postures.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Supine</th>
<th>Right</th>
<th>Left</th>
<th>Prone</th>
</tr>
</thead>
<tbody>
<tr>
<td># of epochs</td>
<td>657</td>
<td>90</td>
<td>52</td>
<td>1</td>
</tr>
<tr>
<td>Sensitivity (%)</td>
<td>94.6</td>
<td>95.0</td>
<td>94.0</td>
<td>—</td>
</tr>
<tr>
<td>PPV (%)</td>
<td>97.9</td>
<td>98.4</td>
<td>97.5</td>
<td>—</td>
</tr>
</tbody>
</table>

Right, right lateral; Left, left lateral; PPV, positive predictive value.

### Table 5. Statistical results of epoch-by-epoch snoring detection.

<table>
<thead>
<tr>
<th># of epoch</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
<th>Accuracy (%)</th>
<th>Kappa statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>953 ± 62</td>
<td>95.7 ± 3.6</td>
<td>84.2 ± 5.9</td>
<td>91.2 ± 2.1</td>
<td>0.80 ± 0.04</td>
</tr>
</tbody>
</table>

Results are presented as mean ± standard deviation.
4. Discussion

4.1. Agreement between the proposed method and reference snoring events

In this study, a fully unconstrained snoring monitoring method using a PVDF sensor was established and evaluated. Snoring signals were measured from the participants without consciously feeling the presence of the sensor installation, and a total of 3392 snore events were correctly detected using the suggested method. The snoring event detection process was performed with the following steps: 1) extraction of the snoring signal from the PVDF data; 2) extraction of spectral features using STFT; 3) classification of snore events with training of the SVM classifier. For algorithm evaluation, LOOCV was adopted, and it was shown that the detected snore events strongly concurred with those from the reference snore signals. In the epoch-by-epoch analysis (see table 5), for all participants, the kappa statistic was greater than substantial agreement ($k > 0.6$). In addition, more than half (6 of 10) of the participants exhibited almost perfect agreement ($k > 0.8$); thus, the overall $k$ was in a borderline case between almost perfect and substantial agreement (Landis and Koch 1977). Consequently, it can be concluded that our proposed method can be used for snoring detection in a sleep monitoring system.

4.2. Comparison with previous studies

The unconstrained PVDF sensor-based method had a higher or similar performance compared with previous microphone-based or constrained PVDF-based methods (see table 3). For example, Duckitt et al used a freestanding microphone to monitor snoring automatically on the basis of hidden Markov models (HMMs), and the results were compared with manually obtained annotations (Duckitt et al 2006). That method classified snore events with 82.2%
sensitivity, which was approximately 10% lower than our results and was vulnerable to detecting a snore in regular breathing sounds or ambient noises. Cavusoglu et al used a microphone that was placed over the subject’s head to detect snoring episodes for simple snorers and OSA patients (Cavusoglu et al 2007). An analysis accounting for ambient noise during sleep was not conducted in that study, and snoring detection performance was lower than that of ours in OSA patients. However, because the method and system we proposed were not applied to simple snorers, the detection performance of our method might change under this condition.

Yadollahi et al used two microphones, one placed over the trachea and the other hung in the air (ambient microphone) to distinguish the normal breathing and snore sounds (Yadollahi and Moussavi 2010). Azarbarzin et al also used two microphones (tracheal and freestanding) to extract the snore sound from the respiratory sound signals of simple snorers and OSA patients (Azarbarzin and Moussavi 2011). In both of those studies, better snoring detection performance was observed when data from tracheal sound recordings were used. However, for tracheal sound recordings, the microphone must be attached or placed over the trachea, and this can cause a great deal of disturbance and inconvenience to sleeping subjects. In addition, noise or vibration caused by body movement could be an important issue for tracheal sound recordings; nevertheless, this was not considered in either study. Emoto et al used a matched pair of microphones for breathing and snoring episode detection in sleep sounds (Emoto et al 2012). Although they used only eight subjects’ data and two microphones, the overall snoring detection sensitivity was approximately 5% lower than our results.

In other previous studies, Shin et al used an air mattress with a balancing tube as a snoring detection sensor (Shin et al 2010). Although they were able to monitor snoring events on the basis of an unconstrained measure, the subjects were instructed to simulate snoring while awake to validate the detection algorithm, and no simple snorers or OSA patients participated in the experiment. Lee et al also used a piezoelectric-based sensor in order to establish a snoring detection method based on HMMs (Lee et al 2013). However, the sensor used in their experiments was attached to the neck during an overnight PSG recording, and this could affect the subjects’ normal sleep because of the inconvenience of the direct electrode attachment. Our proposed method showed better performance, as well as the convenience of unobtrusive measurements compared to the piezoelectric-based sensor method of Lee et al. Norman et al analysed 62 subjects’ PSG data to evaluate the Sonomat, which uses a PVDF film-based sensor, with regard to its capability for diagnosing SRBD, and they verified that the Sonomat can be a reliable device for the detection of snoring events (Norman et al 2014). However, although they used a PVDF-based sensor for snoring detection, all Sonomat events were manually scored in the same manner as PSG scoring because the focus of their research was the validation of the sensor. In this study, we focused on the development of a method for snoring detection using a PVDF sensor.

4.3. Validation of the snoring detection algorithm

In the previous studies using PVDF films as nonintrusive physiological sensors, motion artifacts were considered an important issue because the films are sensitive to minute movements and external vibrations (Choi and Jiang 2006, Baek et al 2012). In this study, we tried to establish an accurate snoring detection method robust to the occurrence of motion artifacts. From table 2, the proposed method classified snore events with an average sensitivity of over 90%, and PPV of over 95%, for both ‘snoring’ and ‘snoring with movement’ epochs. Furthermore, there was no significant difference in the snore event detection results between the SN and SM epochs. One could speculate that the two selected spectral features (PR and PF) were proper features for snore event detection and motion artifact event rejection. The frequency band of
the motion artifact was relatively low compared to that of snoring, and we were able to obtain acceptable results for each SN and SM epoch using this spectral information.

SVM was originally designed for binary classification and is known to perform best for two-group classification problems (Cortes and Vapnik 1995, Hsu and Lin 2002, Manevitz and Yousef 2002). Based on the previous research, we selected SVM, rather than other possible classifiers such as the HMM or artificial neural network, for the binary classification of snore/non-snore events. As a result, we used only two spectral features and a linear SVM classifier to establish a simple, fast, and generalized snoring detection algorithm. Two complementary spectral features were selected, and we found that our method was able to correctly classify snore events with 94.6% sensitivity, despite using only two simple features.

With regard to the sampling rate of the analysis data, we were able to measure the snoring-related vibration from a PVDF sensor with a 250 Hz sampling rate, whereas the microphone-based studies that were referenced in this paper required at least a 10 kHz sampling rate for snoring sound recording, which may be unsuitable for residential or ambulatory monitoring devices. Quantitatively, our method required approximately 4.5 s to process one entire night (approximately 8 h) of PVDF data, whereas a previous microphone-based study required approximately 6 min to process 6 h of data (Cavusoglu et al. 2007). Less than 5 s can be considered as an acceptable processing time for the data from one entire night.

Our method tended to overestimate snore events in the epoch-by-epoch analysis (see table 5 and figure 8). It is considered that our method does not entirely reject motion artifacts that influenced the PVDF signals. As shown in figure 5(b), spectral features during body movement were relatively close to the SVM hyperplane, relative to those from normal breathing. This means that body movement can be more easily misclassified as a snore event in some SVM classifications. In addition, wakefulness during sleep can be related to misclassification of non-snore events because wakefulness is similar to a motion artifact. Another suitable feature that could be selected for motion artifact or wakefulness detection, such as a motion-related frequency band (relatively low-frequency), may improve our method’s accuracy for ‘real’ snoring detection. Alternatively, one could speculate that the proposed method may have misclassified non-detectable levels of snoring signals that were not noted by the observers. Despite these deficiencies, the average snore epoch detection accuracy for one entire night of data was over 90%, and it can be regarded that almost all motion artifact periods were effectively excluded in the analysis process.

During sleep, snoring signal patterns can vary depending on the subject or sleep posture (Oksenberg and Silverberg 1998). To consider these aspects, we analysed the snoring detection algorithm according to three sleep postures (supine, left- and right-lateral), and there were no significant differences in the snore event detection results among these sleep postures (see table 4). From the PVDF data, there was only one snoring or non-snoring epoch of prone posture, and we concluded that it is difficult to sleep in a prone posture during PSG because many electrodes are attached to the subject’s face and body.

4.4. Limitations

This study has some limitations. First, we did not analyse the snoring data from simple snorers (snoring without any kind of sleep apnea). In the analysis, the results from OSA patients with mild severity (such as subject #20), quite similar to the case of a simple snorer, showed more than average sensitivity (95.0%) and PPV (99.5%). Moreover, previous snoring detection studies were able to estimate the simple snorers’ data more accurately compared to the data of OSA patients. We can expand the application of our system using a PVDF sensor to detect simple snorers’ snoring events. Second, other events, such as silence, normal breathing,
and body movement, were classified as non-snore events but were not differentiated from one another. However, unlike snore events, the detailed classification of non-snore events has little clinical significance. Last, the efficacy of the proposed method was not assessed with data acquired in a residential environment. In addition, a realistic sleep situation, such as more than one person sleeping in the same bed, was not considered in this study and serious misclassification of snore events may be caused under this condition. For this case, the use of a sensor for each person will enable individual snoring detection results because the size of the PVDF sensor was designed to fit a single person (30 × 30 cm). To verify this issue, further study will include an assessment of our suggested method in a residential environment or practical situation.

5. Conclusions

In this study, a new snoring monitoring method using a PVDF sensor was proposed that can measure snoring signals from subjects unconstrainedly. Our proposed system enabled accurate, fast, and motion-artifact-robust snore event detection. Furthermore, the suggested method requires neither complex processing nor trained sleep experts, and can be used for real-time snoring detection. With a single setup of this PDVF sensor, snoring and apnea can be monitored simultaneously. We plan to focus our future study on SRBD detection for residential monitoring to examine whether our method can be generalized outside the laboratory as well.

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References

American Academy of Sleep Medicine 2005 The International Classification of Sleep Disorders: Diagnostic and Coding Manual (Westchester, IL: American Academy of Sleep Medicine)


Hoffstein V, Mateika S and Nash S 1996 Comparing perceptions and measurements of snoring Sleep 19 783–9


Landis J R and Koch G G 1977 The measurement of observer agreement for categorical data Biometrics 33 159–74


Lugaresi E, Cirignotta F, Coccagna G and Piana C 1980 Some epidemiological data on snoring and cardiocirculatory disturbances Sleep 3 221–4


Pecker Y, Hedner J, Johansson A and Bende M 1997 Reduced hospitalization with cardiovascular and pulmonary disease in obstructive sleep apnea patients on nasal CPAP treatment Sleep 20 645–53


