Detection of sleep breathing sound based on artificial neural network analysis

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Abstract

Obstructive sleep apnea-hypopnea syndrome (OSAHS) is known to cause daytime drowsiness and an association with diseases such as Type II diabetes, cardiovascular disease, and stroke. A polysomnography (PSG) test is the traditional method for diagnosing OSAHS. However, this test is expensive, inconvenient, and requires the placement of body contact sensors during sleep. Recently, in several studies, the snoring/breathing episodes (SBEs) acquired by non-contact microphones have been used for OSAHS diagnosis. SBEs may range from barely audible to loud. SBE detection, especially low-intensity SBEs, can be challenging in noisy environments because of the low signal-to-noise ratio (SNR). In this paper, we propose a novel method for the rapid detection of low-intensity SBEs from data recorded during sleep. Our method is based on an artificial neural network (ANN) technique. When an ANN is trained as subject-specific classifier, we show that the proposed method can classify low-intensity SBEs and low-intensity non-SBEs that may occur during actual sleep with an average accuracy of 75.10%.

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1. Introduction

Obstructive sleep apnea-hypopnea syndrome (OSAHS) is characterised by the recurrence of airflow cessation in the upper airway (UA) during sleep owing to the complete or partial obstruction of the UA. This causes oxygen desaturation and nocturnal awakening. OSAHS increases the risk of cardiovascular complications [1] such as hypertension, ischemic heart disease, cerebral stroke, and neurocognitive dysfunction. It has been estimated that the prevalence of OSAHS is 3–7% among adult men and 2–5% among adult women [2]. The current reference standard method for OSAHS diagnosis is a full-night polysomnography (PSG) test. This requires the attachment of breathing sensors (oral thermistor, nasal pressure cannulas, and chest belt) directly to the body. Research has found that the sleep efficiency, the spectral power in an electroencephalogrameeEG), and rapid eye movement are influenced during the first night of PSG owing to the discomfort and restricted movement that results from the numerous sensors attached to the patient [3–6].

Snoring is a breathing noise caused by vibration of the soft palate and the uvula; it is the earliest and the most common symptom of OSAHS [7,8]. Snoring analysis can provide a significant advantage over PSG in diagnosing OSAHS. Since snoring can be conveniently acquired with low-cost equipment, several studies have proposed snoring analysis methods as an alternative to PSG [9,10]. These methods can detect snoring in sleep sounds with high accuracy; however, they require microphones to be placed on the trachea during sleep, which causes discomfort and inconvenience to patients.

In recent studies, sleep sounds were recorded using a non-contact microphone. These studies have developed snore features [11–23] and integrated snore features [18] to characterize the OSAHS condition. The potential of snore sound analysis in estimating the severity of OSAHS is quite well established now through our previous work as well as the work of many independent and highly reputed research groups throughout the world [11,12,14,18–23]. It

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is well established that snore sound analysis can diagnose OSAHS at a sensitivity and specificity of approximately 90% simultaneously, in comparison to the standard diagnosis through clinical PSG [e.g.,12,14,18,19,23]. Furthermore, several recent studies [24–26] have provided evidence that sleep-wake activity and sleep quality parameters can be estimated based on the analysis of breathing sound obtained during sleep. These results highlight the importance of detecting snoring/breathing episodes (SBEs) from sleep sound recordings.

SBE segmentation is a pre-requisite for snore-analysis based diagnosis of OSAHS. Existing automatic SBE detection methods commonly identify sound episodes in sleep sound recordings and then classify the identified sound episodes as SBEs or non-SBEs [9,10,27,28]. To detect sound episodes, methods such as the short-time energy (STE) and zero-crossing rate (ZCR) are usually employed [9,14,15,16,27]. However, our previous work showed that these techniques are unsuitable for detecting sound episodes under low signal-to-noise ratio (SNR) conditions [29]. SBEs may have a wide dynamic range of more than 95 dB. Hence, SBE detection is challenging in low-SNR conditions because noisy environments tend to cause significant detection errors. A recent sleep study reported the detection/analysis of low-intensity breathing by using a non-contact microphone [30]. However, the method may be complex to implement as it requires a pre-processing step to subtract background noise segments from the audio signal and a step to detect events by using a signal-energy-based method.

In order to reliably evaluate the variability of an individual’s SBEs, the detection of low-intensity SBEs is required. Hence, developing an automatic, simple, and accurate detection method would be advantageous.

We have developed a technique based on an artificial neural network (ANN) that can detect SBEs from sleep sounds recorded using a contactless single-channel microphone [29]. As far as we know, no other method that can directly extract SBEs buried in the noise floor has been proposed in sleep studies. This method can detect low-intensity SBEs with a high degree of accuracy. However, this method is based on the analysis of weight vectors of a trained ANN, as a way of obtaining information from a signal that the ANN has been trained to predict (in the sense of the time series prediction). The method differentiated SBE and non-SBE classes based on the information embedded in the weight vectors of multiple ANNs trained through a training phase, and thus requires ample computation time owing to the training phase of multiple ANNs. The method still requires a long processing time on today’s fastest computer and is too slow for practical use.

Therefore, in this paper, we explore the hypothesis that the enhanced ANN-based technique can be accurately and faster in detecting low-intensity SBEs, including those that are buried in the background noise floor, in sleep sounds. In this study, we enhance the ANN-based detection technique via binary classification, wherein 0 and 1 represent non-SBE and SBE classes, respectively. This will help reduce the calculation time. In this way, we can use the testing phase in the ANN-based SBE detection. The originality of our new work is the proposal of using an ANN as an effective time series classifier for rapidly detecting low-intensity SBEs in sleep sounds. The usefulness of the proposed method is shown by analysing sounds recorded overnight from patients undergoing a routine PSG study in a hospital. Several researchers have indicated that SBE-based analysis might potentially be a non-contact approach for sleep-wake evaluation and OSAHS screening [11–14,18–26]. The ability to detect the presence of SBEs in this study will be useful in establishing whether a person is snoring, independent of the intensity, in other words, the detection of the apnea (silence) segment in sleep sounds. Non-contact approaches are being developed as alternative cost-effective approaches for OSAHS diagnosis. By incorporating these techniques along with SBEs efficiently obtained through this work, a more accurate diagnosis of OSAHS and sleep stage evaluation may be achieved.

2. Method

2.1. Snoring and Breathing episodes

Sleep sounds were recorded during a PSG test at Anan Kyoei Hospital (Tokushima, Japan). The nominal distance from the microphone (Model NT3, RODE-NT3, Sydney, Australia) to the mouth of the patient was 50 cm, but it could vary from 40 cm to 70 cm owing to patient movements. Sound data were recorded at a sampling frequency of 44.1 kHz with a digital resolution of 16-bit samples through a microphone pre-amplifier (Mobile pre USB, M-Audio, California, USA) and computer. As we needed to identify sound episodes under low-SNR conditions, SBEs were identified from sleep sounds through a careful listening process. Human perception and categorisation of the sounds were used as the gold standard. From the sleep sounds, the start and end points of the SBEs were identified by three human observers who participated in the sleep-sound-based studies. These points were averaged, and the average values were used to determine the length of the SBE. The background noise was also identified by the human observers. To justify the reliability of annotation, the inter-annotator agreement of the three human judges was calculated based on Cohen’s kappa [31,32].

The SNRs of the SBEs included in the sleep sounds can be calculated as follows:

\[
\text{SNR [dB]} = 10\log \frac{P_S}{P_n},
\]

where \(P_S\) is the power of the SBE, and \(P_n\) represents the power of the background noise. As the recorded data contain several SBEs, the average SNR is used as a representative value in this study. Since we have shown that the middle-frequency band of 5–10 kHz carries information on OSAHS [13], the records used were downsampled by a factor of 2–22.05 kHz. The study has been approved by the ethics committees of Tokushima University and Anan Kyoei Hospital.

2.2. Proposed ANN-Based SBE detection method

In this section, we describe a new ANN-based method to quickly detect SBEs from sleep sound recordings. The new method proposed in this work uses first-short sleep sounds for the training phase of the ANN and uses the remaining sleep sounds for the test phase of the ANN.

The sleep sound \(x(n)\) is divided into a segment length \(M\) and an overlap \(L\) (the \(j\)-th segment is denoted by \(x_j(n)\)). In the ANN, we use a three-layer perceptron trained with the error back propagation method. The ANN consists of three layers: the input, hidden, and output layers. The number of units in the input, hidden, and output layers are \(P_i\), \(P_h\), and 1, respectively. The activation functions of the hidden and output layer units are hyperbolic tangent and linear functions, respectively. Note that the hyperbolic tangent function is employed to model the non-linear relationship between the input and the output. For the training phase, the error backpropagation method is based on the Levenberg–Marquardt method and is used to measure the increase in speed [33].

In the proposed method, the ANN is trained with an early stopping procedure by using the training dataset created from the first short sleep sound (Input signal: \(x_j(n - 1), x_j(n - 2), \ldots, x_j(n - L_j)\)). Target signal: \(y_j(n), j = 1, 2, \ldots, K\). Here, the target signal is either 1 or 0, corresponding to the sound activity and background noise determined by the manual labelling process described in Section 2.1. In the early stopping procedure, the training dataset is randomly divided into the following three subsets: 70% for training
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