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SVM-based Efficient Sleep States Classification and Management Derived from Breath Sound Measurements

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Abstract: Breath sounds (BS) contain important physiological indicators, making their analysis and detection a well-established area of study. This paper proposes a method for identifying and classifying sleep stages based on the spectral power and spectral flux of breath sounds. These multiple features effectively capture the characteristics of breath sounds, enabling efficient classification of data related to both normal and abnormal breath sounds. We employ support vector machine (SVM) classification models to achieve automatic, high-efficiency classification using the spectral characteristics of breath sounds. The high classification accuracy obtained validates the performance of the proposed feature sets and classification model. Additionally, the experimental results demonstrate that breath sounds can be used to evaluate sleep states as an alternative to commercial products.

Keywords: Sleep States, Breath Sound, Spectrum Characteristics, Multiple Features, SVM.

1. Introduction

Sleep state classification has always relied on analyzing recordings of physiological data to create a hypnogram, which identifies various sleep conditions. This analytical process typically adheres to established standards for categorizing sleep states, such as those outlined in [1], where each 30-second segment is classified as wake, S1–S4, or REM. A more contemporary classification approach, put forward by the American Academy of Sleep Medicine (AASM) in 2007 [2], merges the non-REM stages S3 and S4 into a single deep sleep stage referred to as N3.

While the hypnogram remains the gold standard, recent years have seen a surge in research focused on developing automatic or semi-automatic methods for assessing sleep conditions [3-5]. Despite the promising results achieved thus far, there remains significant room for improvement-particularly considering the time-consuming and labor-intensive nature of visual sleep scoring. Current technologies extract a broad range of physiological features from polysomnographic (PSG) signals, encompassing time-domain, frequency-domain, and combined time-frequency-domain characteristics. However, some state-of-the-art approaches rely on just one or two features for sleep condition classification [6]. Beyond the specific electrophysiological features utilized, existing methods also vary in their choice of classification algorithms. Machine learning techniques such as artificial neural networks have been widely employed for sleep state discrimination [7-9], while Bayesian probability-based classification methods have also found application in sleep staging [10].

In this study, we propose a sleep stage classification approach for the sleep database presented herein, utilizing a support vector machine (SVM) as the classifier. SVM training and classification algorithms were applied to the sleep database introduced in this paper. Sensitivity (Se) was evaluated from the classification results, along with positive predictivity (P+). The average classification accuracy was also computed. The findings demonstrate that the proposed method effectively discriminates between different sleep states.

2. Experimental Approaches

The sleep states classification process can be divided into two parts, the features extraction part and the classification part. In the extraction part, the breath sound is processed in order to obtain envelop waveform extraction, and then, features are extracted by our method which were proposed in following, then built sleep stages database based on SleepScan (TANITA SL-503) which is a mat placed under bedding to monitor sleeping conditions and breath sound waveform [11]. The database is used as the training data and other input data is used as the testing data. In the classification part, the training data is used by the SVM system to find the optimum hyperplane separating sleep stages. Then, the separating hyperplane is applied to the testing data to obtain the classification. Then, the classifier system have functions for predicting and assessing sleeping conditions.

The process of sleep state classification can be split into two components: feature extraction and classification. For the feature extraction component, breath sounds are first processed to extract envelope waveforms. Subsequently, features are derived using the method proposed later in this work. A sleep stage database is then constructed based on data from SleepScan (TANITA SL-503)—a mat placed under bedding that monitors sleep conditions and captures breath sound waveforms [11]. This database serves as the training data, while other collected data is used as testing data. In the classification component, the SVM system utilizes the training data to identify the optimal hyperplane for distinguishing between different sleep stages. This hyperplane is then applied to the testing data to perform classification. Additionally, the classifier system is equipped with functions to predict and evaluate sleep conditions.

2.1. Data Collection and Pre-processing

During the collection of breath sound (BS) signals, the data is captured directly from participants using Bluetooth-enabled recorders. The acquired BS data originates from multiple sources and is stored in diverse formats. To support subsequent analytical processes, the recorded BS signals are resampled to a frequency of 4210 Hz with a 16-bit resolution. Following resampling, the normalized BS data is divided into overlapping frames of a fixed length. Specifically, in our experiment, each frame contains 256 samples, with a 25% overlap between consecutive frames; additionally, a Hamming window is applied to each frame to optimize signal processing [12].

2.2. BS Features

(1) Spectrum power: The logarithm of the total spectrum power is used, that is, F(w) is the power of the frequency, and w0 is half of the sampling frequency:

$$\mathrm{SP} = \log\left(\int_0^{w_0} |F(w)|^2 dw\right) \tag{1}$$

(2) Spectral flux: Spectral flux is denoted as the spectrum variation value between the two neighboring frames in a short time window.

Different parameters will lead to signal variations, and affect the classification performance. To reduce this effect, the peaks, spectrum power and spectrum flux are normalized. In this work, 4 features are considered to be used for the evaluation of sleep stages. For every epoch, 4 features detailed is shown in Table 1, are associated.

The sleep stages are defined every 30-s, as same as SleepScan which measured data every 30-s one time. Then, for every epoch time of 30-s length, 6 features are extracted. We try to summarize and find patterns by statistical analysis methods in the algorithm about these breath characteristic parameters.

Table 1. List and description of features.

Features	Description of the feature
1	Mean of spectrum power
2	Standard deviation of spectrum power
3	Mean value of spectrum flux
4	Standard deviation of spectrum flux

2.3. Sleep Stages Database

In this work, we built sleep stages database. Example of SleepScan result with parameters is shown in Table 2. Stage is the sleep stage in this point, 4,3,2,1 are awakening, REM, shallow, deep, respectively. Time of in the list is 30-s length, one night have 700 points total 5 hours in generally.

Table 2. Example of SleepScan all-night sleeping condition result with parameters.

Time	respiration	heart_rate	stddev	body_movement	Stage
0	5	34	391.1	1	4
30	7.2	33.8	401.4	0	2
60	7.7	37	105.4	0	4
90	7.9	30.7	109.6	0	4
120	7.2	30.6	104	0	4
150	7	23	108.7	0	2
180	7.4	30.2	110.2	0	2
210	7	28.5	85	0	2
240	6.6	28.1	95.5	0	2
270	6.7	28.5	90.6	0	2
300	6.6	28.6	86.9	0	2
330	6.6	29	81.8	0	2
360	6.4	28.9	70.3	0	2
...	...	...	...	...	...

Then, we choose the same stage in the same time by comparing all-night breath sound waveform with all-night SleepScan result, process of comparing same sleep stages is shown in Fig. 2, “D” is deep sleep labeled by value 1, “A” is awakening, “C” is shallow sleep, “B” is REM stage, the result of this process is indicated in Table 3 (marked by red label). At last, Sleep stages database is shown in Table 4.

Table 3. The process of comparing same sleep stages.

SleepScan stage	Breath waveform	Feature 1	Feature 2	Feature 3	Feature 4
4	4	0.75759	0.094767	0.10222	0.013118
4	4	0.79407	0.10916	0.10431	0.015111
4	4	0.82714	0.057828	0.11046	0.0090261
4	4	0.79159	0.069908	0.10259	0.0090519
4	4	0.68365	0.14652	0.10244	0.0086982
4	4	0.45619	0.27529	0.10043	0.0091338
4	4	0.2464	0.19577	0.096098	0.0047827
2	4	0.11507	0.066309	0.096432	0.0025334
2	4	0.067334	0.024195	0.10238	0.0066548
2	2	0.067747	0.021086	0.1072	0.0055532
2	2	0.07343	0.020533	0.10799	0.0046467
2	2	0.080855	0.028087	0.10057	0.010482
2	2	0.063139	0.031169	0.098416	0.0096069
2	2	0.076902	0.049865	0.10596	0.0068654
2	2	0.059018	0.041806	0.091183	0.013805
2	2	0.072853	0.032212	0.10211	0.012568
2	2	0.08351	0.043046	0.10652	0.0053211
2	2	0.085056	0.043059	0.10726	0.0054672
2	2	0.045177	0.035079	0.099379	0.013155
2	2	0.025531	0.017189	0.091742	0.012399
2	2	0.039087	0.016263	0.096492	0.01295
4	2	0.056633	0.019446	0.1028	0.0060495
2	2	0.07602	0.07676	0.1028	0.0074329
2	2	0.15947	0.1203	0.10336	0.0076787
2	2	0.28621	0.10774	0.1023	0.006867
2	2	0.32148	0.14955	0.096823	0.0095091
2	2	0.30052	0.155	0.098331	0.0095697
2	2	0.32404	0.15044	0.1011	0.0065072
2	1	0.33685	0.17751	0.10106	0.0092641
2	1	0.2973	0.17709	0.098169	0.0092052
2	1	0.49124	0.1541	0.09896	0.010305
1	1	0.52762	0.12655	0.10355	0.0085656
1	1	0.49084	0.10802	0.10227	0.0047024
1	1	0.46759	0.082926	0.099617	0.0031349
1	1	0.39545	0.079769	0.10011	0.0042084
1	1	0.36847	0.07078	0.10145	0.0042935
1	1	0.37343	0.082132	0.095784	0.007922
1	1	0.42127	0.114	0.094596	0.0075743
1	1	0.5181	0.14508	0.10135	0.0067959
...	...	...	...	...	...

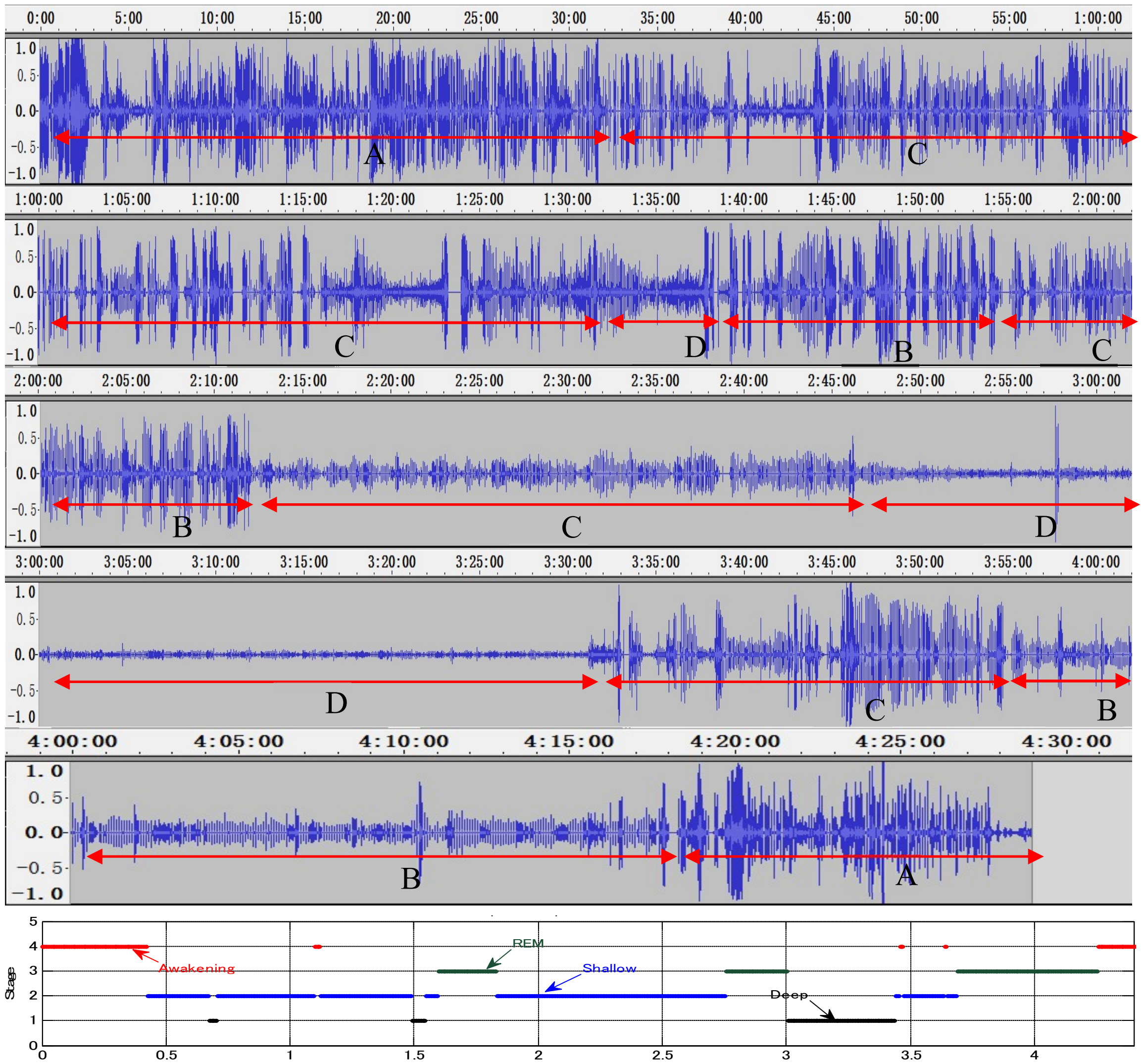

Fig. 4. The upper figure is all-night breath sound signal and estimated sleeping (Y-axis unit is 11025Hz) (A, B, C, D are indicating wake, REM, shallow, deep), the lower figure is sleeping condition measured by SleepScan.

Table 4. Sleep stages database.

Feature 1	Feature 2	Feature 3	Feature 4	Stage
0.92123	0.029251	0.12839	0.014359	4
0.88724	0.028779	0.12353	0.01017	4
0.8662	0.014628	0.11916	0.0069585	4
0.8577	0.019589	0.11851	0.011276	4
0.72479	0.051488	0.10734	0.010634	3
0.71104	0.068975	0.10722	0.0081884	3
0.53707	0.21254	0.1043	0.0098996	3
0.47267	0.20461	0.10052	0.0096539	3
0.64624	0.18856	0.10534	0.0078621	3
0.71896	0.11666	0.10027	0.0086245	3
0.7492	0.051446	0.10515	0.011522	3
0.69932	0.095704	0.102	0.0070919	2
0.61305	0.17603	0.094001	0.009952	2
0.52522	0.13796	0.094472	0.010555	2
0.4388	0.11251	0.10508	0.0063877	2
0.31322	0.066732	0.10828	0.0044017	2
0.69932	0.095704	0.102	0.0070919	2
0.34866	0.041531	0.10664	0.004839	1
0.33531	0.039833	0.10798	0.0030098	1
0.31735	0.017049	0.10666	0.004975	1
0.32373	0.014523	0.10355	0.0046526	1
…	…	…	…	…

Along with experiments, sleep stages database can combine more data to as training set, more samples in database meaning more accuracy, then our system have study function by self. Up to now, sleep stages database have about 8000 points corresponding parameters and stages. The description of SVM is given subsequently.

3. Support Vector Machine Classifier System

Support vector machine (SVM) is a widely used powerful learning machine. It can be used for training, classification and regression. First introduced by Cortes and Vapnik [13], it is based on the simple idea of finding an optimal hyperplane, separating different classes using a number of patterns (features), with maximum margin between the training set and the decision boundary. In the following a simple mathematical introduction of SVM, for more details see [14].

4. Results

In order to evaluate the performance of our algorithm, we tested it on the sleep stages database. We used sleep stages database to estimate one all-night sleeping condition, so we can predict and estimate sleeping condition using sleep stages database. Details of the number of, deep sleep, shallow sleep, REM, wake, training and testing data number of epochs in each all-night are presented in the Table 5. The reliability of our algorithm was assessed by the sensitivity Se and the positive predictivity P+ as follows:

$$S_e = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \tag{2}$$

$$P_+ = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \tag{3}$$

Table 5. Summary of sleep stages database and testing data.

Sleep stages database				Testing Data (sleep stage measured by SleepScan)				Date
Deep	Shallow	REM	Wake	Deep	Shallow	REM	Wake	
2500	2500	2500	2500	105	348	128	52	11/09
				106	440	133	65	11/12
				55	283	231	76	11/14

Where TP, FP, FN are explained as follows:

True positive (TP): the number of well classified this epochs;

False positive (FP): the number of epochs classified this stage (but actually other stage);

False negative (FN): the number of epochs classified other stages (but actually this stage).

The sensitivity Se is defined as the ability of the algorithm in the classification of sleep stages. The positive predictivity P+ is defined as the ability of the algorithm to discriminate this stage between other stages. A good classifier should have high sensitivity and positive predictivity values that should be nearly of the same order. Then, we put into three all-night data as testing data, the three days total result of SVM algorithm are list in the Table 6. Table 7 - 9 are concrete result. In the Table 7- 9, the upper horizontal axis is the stage of data in initially which calculated by SleepScan, the left side vertical axis is the stage of SVM system estimation value.

Table 6. The result of SVM system.

Date	Result	Testing Data (all-night)			
		Deep	Shallow	REM	Wake
11/09	SleepScan	105	348	128	52
	SVM	102	343	135	53
11/12	SleepScan	106	440	133	65
	SVM	114	455	127	57
11/14	SleepScan	55	283	231	76
	SVM	87	235	269	54

Table 7. The concrete result of SVM system(11/09).

Value (Stage)	1 (Deep)	2 (Shallow)	3 (REM)	4 (Wake)
1 (Deep)	92	5	8	0
2 (Shallow)	5	5	116	2
3 (REM)	5	333	10	0
4 (Wake)	0	0	1	51

Table 8. The concrete result of SVM system(11/12).

Value (Stage)	1 (Deep)	2 (Shallow)	3 (REM)	4 (Wake)
1 (Deep)	89	5	12	0
2 (Shallow)	17	23	93	0
3 (REM)	8	421	19	1
4 (Wake)	0	6	3	56

Table 9. The concrete result of SVM system(11/14).

Value (Stage)	1 (Deep)	2 (Shallow)	3 (REM)	4 (Wake)
1 (Deep)	67	1	8	0
2 (Shallow)	18	16	248	1
3 (REM)	2	215	13	1
4 (Wake)	0	3	0	52

According to the equations (2), (3), calculated the summary results for reliability of SVM system are list in Table 10-13, Deep, Shallow, REM, Wake, respectively. Reliability mean value of our algorithm is list in Table 14.

Table 10. Summary results for reliability of our algorithm (Deep).

Date	TP	FP	FN	Se(%)	P+(%)
11/09	92	10	13	87.6	90.2
11/12	89	25	17	83.9	78.1
11/14	67	20	9	90.5	77

Table 11. Summary results for reliability of our algorithm (Shallow).

Date	TP	FP	FN	Se(%)	P+(%)
11/09	333	10	15	95.7	94.4
11/12	421	34	28	93.8	92.5
11/14	215	20	16	93.1	91.5

Table 12. Summary results for reliability of our algorithm (REM).

Date	TP	FP	FN	Se(%)	P+(%)
11/09	116	19	12	90.6	85.9
11/12	93	34	40	70	73.2
11/14	248	22	35	87.6	91.9

Table 13. Summary results for reliability of our algorithm (Wake).

Date	TP	FP	FN	Se(%)	P+(%)
11/09	51	2	1	98.1	96.2
11/12	56	1	9	87.5	98.2
11/14	52	2	3	94.5	96.3

Table 14. Reliability mean value of our algorithm.

Mean value		
Stage	Mean S_e (%)	Mean P_+ (%)
Deep	87.3	81.8
Shallow	94.2	92.8
REM	82.7	83.7
Wake	93.4	96.9

5. Conclusion

The reliability mean value of our algorithm obtained for the set of 4 features are presented in Table 14. Our results show that the SVM model classifies the majority of stages with high sensitivity. In addition, the results shown in the Table 14 are divided into four stage: Deep representing deep sleep (Se=87.3%), Shallow representing shallow sleep (Se=82.7%) and REM representing rapid eye movement (Se=94.2%); Wake have Se is 93.4%. The positive predictivity P+ are 81.8%, 83.7%, 92.8%, 96.9%, corresponding to Deep, Shallow, REM, Wake, respectively. Then it appears that our classifier is better to be used with subjects.

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