



## Sleep Breathing Disorders Detection with Bioradar Using a Long Short-Term Memory Network

Lesya Anishchenko<sup>\*(1)</sup>, Ludmila Korostovtseva<sup>(2)</sup>, Mikhail Bochkarev<sup>(2)</sup>, and Yuri Sviryayev<sup>(2)</sup>

(1) Bauman Moscow State Technical University, Moscow, Russia

(2) Almazov National Medical Research Centre, St. Petersburg, Russia

### Abstract

Development of effective non-contact ways for long-term sleep respiratory-related sleep disorders detection, which may indicate the presence of different health and life-threatening conditions, is an up-to-date task of sleep medicine. The paper presents a device for remote long-term sleep respiration pattern monitoring based on the analysis of a bioradar signal and processing algorithm for detection respiratory-related sleep disorders. The method was validated utilizing data of 15 volunteers, which underwent a sleep study in a sleep laboratory of Almazov National Medical Research Centre. The proposed method is based on the usage of a long short-term memory network to detect breathing disorders during sleep. We achieved accuracy and Cohen’s kappa of 0.97 and 0.80 for respiratory-related sleep disorders classification, respectively. The results might be used while creating new methods for remote detection of sleep movement disorders.

### 1 Introduction

High quality sleep is one of the most important biological necessities of a healthy and active life. The decrease in the sleep quality may be caused by various sleep disorders: insomnia, obstructive sleep apnea, periodic limb movements, etc.). One of the most severe sleep disorders are the respiratory-related sleep disorders such as obstructive sleep apnea (OSA), central sleep apnea (CSA) [1]. These discoverers in the short term may affect the well-being, fit to work, increase daytime sleepiness and fatigue [2]. In the long term they increase the risk of such socially significant health problems as cardiovascular diseases [3, 4], obesity [5], diabetes mellitus [6], and depression [7]. A precise daily evaluation of sleep quality and sleep disorders detection at the early stages of the disease can help to prevent different health problems, attract the patient’s attention to his/her health and provide measurable feedback which will increase motivation to follow the physician’s recommendations.

At present, the “gold” standard for sleep breathing disorders diagnostics is an overnight polysomnography (PSG). Its data are used to estimate the apnea–hypopnea index (AHI), that is a number of respiratory-related sleep events (RRSE) per hour of sleep [1], and thus to measure the severity of

the sleep breathing disorders. The PSG method requires usage of electrodes, wires and chest belts that limit patient’s movements during sleep and cause discomfort, which may influence on sleep monitoring results. Therefore, there is a need for noncontact sleep monitoring devices suitable for long-term home-use.

One of the promising methods for sleep diagnostics is a bio-radiolocation (BRL), which is based on remote registration of a bioradar signal’s modulation caused by movements of a human body and visceral organs [8]. Although there are a few papers dedicated to the processing of bioradar data for detecting sleep breathing disorders [9, 10] and estimating sleep stages [12, 11], usually they provide results for testing mainly on patients with moderate or severe obstructive sleep apnea syndrome (OSAS), while the correct detection of RRSE for persons with AHI<15 remains a challenging task. In present work we proposed a bioradar data processing algorithm tested on the experimental data which may help to overcome this problem.

### 2 Experiments and Methods

The experiments were conducted at Almazov National Medical Research Centre in 2019. Fifteen volunteers with different severity of respiratory-related sleep disorders which underwent a sleep study in a sleep laboratory were examined. Experimental study was approved by the Ethical Committee of Almazov National Medical Research Centre. Characteristics of the studied subjects are listed in Table 1.

**Table 1.** Subjects Characteristics

<b>Number of volunteers</b>	15
<b>Age, years</b>	20–81 (45.2 ± 18.4) *
<b>Gender (male/female)</b>	8/7
<b>Body Mass Index, kg/m<sup>2</sup></b>	17.3–40.4 (26.1 ± 7.4) *
<b>PSG Record Duration, min</b>	309.5–588.5 (410.9 ± 71.4) *
<b>Apnea–Hypopnea Index, events/ events per hour</b>	1–580 (117.4 ± 185.9)/ 0.1–93.5 (17.8 ± 28.4) *

\* min–max (mean ± std)

During the experiments, PSG and BRL signals were recorded simultaneously. The full-night PSG signals were collected with Embla N7000 system (Natus Neurology Inc., USA). For recording bioradar signals the BioRASCAN-24 radar designed at Remote Sensing Laboratory at Bauman Moscow State Technical University was used. Its architecture is based on a concept of low-cost portable bioradar given in [14]. The technical characteristics of the bioradar are presented in Table 2.

**Table 2.** Technical Characteristics of BIORASCAN-24 Radar

Parameters	BioRASCAN-24
Probing signal	Continuous wave
Probing frequency, GHz	24.0
Detecting signal band, Hz	0.1–15
Radiated power density, $\mu\text{W}/\text{cm}^2$	$<3$
Beam aperture, Size, mm	80 / 34
	95x75x45

The maximum power density radiated by the radar is less than  $3 \mu\text{W}/\text{cm}^2$  thus satisfying the Russia safety standard for microwave emission, which is  $25 \mu\text{W}/\text{cm}^2$  in the frequency range of 3–300 GHz (for 8 hours exposure and more) [15]. The bioradar was located at 1.2 m above the floor at a distance of approximately 1.5 m for a lateral view in relation to the volunteer. The transceiver antennas were directed to the volunteer's thorax and abdomen (Fig. 1).



**Figure 1.** Photo of the experiment.

Recording of PSG and BRL signals was started in the evening and stopped in the morning by the somnologist. The classification of each RRSE in the PSG record was done by a somnologist according to recommendations of the American Academy of Sleep Medicine [16].

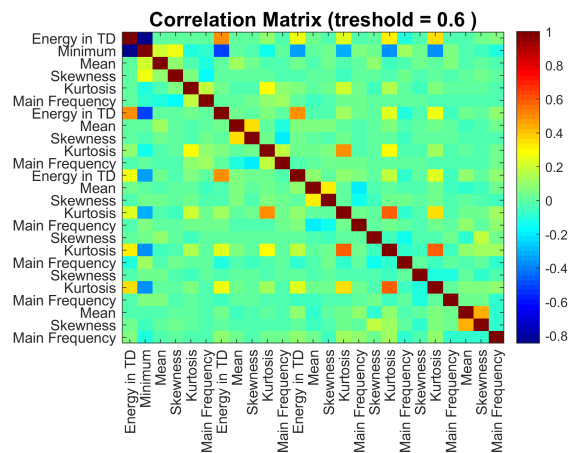
### 3 Data Processing

The data processing algorithm consisted of the following stages: the BRL signal processing, feature extraction. The

extracted features were then used to train a long short-term memory (LSTM) network to detect in the BRL signal such RRSE as OSA, CSA, mixed sleep apnea(MSA) and hypopnea(HYP), which all are used for estimating AHI. The processing of the recorded BRL signals was done in Matlab 2019a.

During the BRL processing stage, we used Principal Component Analysis to extract from two bioradar quadratures (I and Q) a single signal for further analysis. To form a feature vector the following parameters for the extracted principal component were estimated in the window of 1s width: energy, amplitude, fundamental frequency, maximum, minimum, standard deviation, median, skewness, kurtosis, mean. Each parameter was estimated in five frequency ranges 0.05–0.5 Hz, 0.5–1 Hz, 1–2 Hz, 2–5 Hz, over 5 Hz. The feature vector for each window was marked according to the classification made by a somnologist for PSG signals as 'RRSE' and 'not RRSE' for episodes with or without any of the following RRSE: OSA, CSA, MSA, HYP.

Before training the classifier we made the correlation analysis to select only features with correlation coefficient lower than 0.6. Remained 25 features (Fig. 2) were used for training the LSTM network .



**Figure 2.** Features Correlation Matrix.

### 4 Classification Results

To perform RRSE/not RRSE classification for bioradar data we trained a deep LSTM neural network to classify each time part of sequence data represented as a feature vector.

In total, the experimental dataset consisted of data for 15 volunteers (10873 sequences) and was divided into training, validating and testing datasets as follows:

- training dataset contains the data for 8 volunteers: 3 volunteers with severe OSAS, 2 with medium OSAS and 3 healthy volunteers;

- validating dataset contains the data for 3 volunteers: 2 volunteers with severe OSAS and 1 healthy volunteer;
- testing dataset contains the data for 4 volunteers: 1 volunteer with mild OSAS and 3 healthy volunteers.

Each sequence has 25 features and 5000 time samples in length which correspondences to 5000 s.

To prove that the proposed classifier is suitable for healthy volunteers and patients with mild OSAS the test dataset contains data for 3 healthy volunteers and 1 volunteer with mild OSAS, which are the most challenging cases for automatic OSAS severity estimation by means of non-obtrusive sleep monitoring methods.

We used LSTM network with a bidirectional layer containing 200 hidden units. The input for the LSTM was set to be a sequence of feature vector size which is 25, and output was the full sequence. As we have two classes ('RRSE' or 'not RRSE') a fully connected layer of size 2 was used, followed by softmax and classification layers.

For training we chose the solver 'adam'. 'MiniBatchSize' parameter was set to be 10 and training was done for 40 epochs. The learning rate was set to 0.001, and the gradient threshold – to 2 to prevent the gradients from exploding.

The classification results for the test data set are given in the Table 3 as a confusion matrix. To estimate the classifier performance we used the following metrics: accuracy, sensitivity, specificity and Cohen's kappa. The later was used because it is known to be a more reliable metric (comparing to an accuracy) of classifier performance in case of the unbalanced datasets such as the one used in the present work.

As can be seen from the Table 3, the SBD classification accuracy and the Cohen's kappa for the proposed LSTM network are 97 and 80 %, respectively.

**Table 3.** Classification Results

		Predicted Class	
		not RRSE	RRSE
True Class	not RRSE	22 289 068	442 087
	RRSE	391 095	9 723 340
<b>Accuracy, %</b>		97.4 ± 4.0	
<b>Sensitivity, %</b>		98.8 ± 0.9	
<b>Specificity, %</b>		98.0 ± 2.3	
<b>Cohen's kappa, %</b>		80.0 ± 33.7	

## 5 Conclusion

In this paper we presented the method for remote unobtrusive respiratory-related sleep disorders detection based on

the analysis of a bioradar signal by means of a LSTM network, which was tested on a clinically verified BRL data and achieved classification accuracy and Cohen's kappa of 0.97 and 0.80, respectively. It should be noted that the results achieved for the most challenging types of subjects: healthy volunteers and patient with mild OSAS.

Several limitations of the present study should be mentioned. First, the results may be biased due to relatively small number of participants. Second, all experiments were carried out in the same surroundings. Therefore, in future, we are planning to enrich the dataset with experimental data for different surroundings and orientations of bioradar toward the subject and to evaluate the clinical utility of the proposed method to be used both in different sleep centers and at home.

## 6 Acknowledgements

The reported study was funded by RFBR according to the research project No. 18-29-02013.

## References

- [1] "International classification of sleep disorders, revised: Diagnostic and coding manual". Chicago: American Academy of Sleep Medicine, 2001.
- [2] Fortier-Brochu, E., Beaulieu-Bonneau, S., Ivers, H., Morin, C. M., "Relations between sleep, fatigue, and health-related quality of life in individuals with insomnia," *J Psychosom Res*, Vol. 69, No. 5, 475–83, 2010.
- [3] Koo, D.L., Nam, H., Thomas, R.J., Yun, C.H., "Sleep Disturbances as a Risk Factor for Stroke," *J Stroke*, Vol. 20(1), 12–32, 2018.
- [4] Boulos, M.I., Murray, B.J., Muir, R.T., et al., "Periodic Limb Movements and White Matter Hyperintensities in First-Ever Minor Stroke or High-Risk Transient Ischemic Attack," *Sleep*, Vol. 40(3), 2016.
- [5] Gangwisch, J.E., Gangwisch, D., Boden-Albala, B., "Inadequate sleep as a risk factor for obesity: analyses of the NHANES I," *Sleep*, Vol. 28, 1217–1220, 2005.
- [6] Ramos, A.R., Wallace, D.M., Pandi-Perumal, S.R., et al., "Associations between sleep disturbances and diabetes mellitus among blacks with metabolic syndrome: Results from the Metabolic Syndrome Outcome Study (MetSO)," *Ann Med*, Vol. 47(3), 233–237, 2015.
- [7] Chan, J.W., Lam, S.P., Li, S.X., et al., "Eveningness and insomnia: independent risk factors of nonremission in major depressive disorder," *Sleep*, Vol. 37(5), 911–917, 2014.

- [8] Anishchenko, L., et.al., "Application of step-frequency radars in medicine," *Proceedings of SPIE 9077 Radar Sensor Technology XVIII*, Vol. 90771N, 2014.
- [9] Du, N., Liu, K., Ge, L., & Zhang, J., "ApneaRadar: A 24GHz Radar-Based Contactless Sleep Apnea Detection System," in 2017 2nd International Conference on Frontiers of Sensors Technologies (ICFST), 2017, April, pp. 372–376.
- [10] Alekhin, M., et.al., "A novel method for recognition of bioradiolocation signal breathing patterns for noncontact screening of sleep apnea syndrome," *International Journal of Antennas and Propagation*, 2013.
- [11] Zhang, F., Wu, C., Wang, B., Wu, M., Bugos, D., Zhang, H., & Liu, K. R., "Smars: sleep monitoring via ambient radio signals," *IEEE Transactions on Mobile Computing*, 2019.
- [12] Tataraidze, A., Anishchenko, L., Korostovtseva, L., Kooij, B. J., Bochkarev, M., & Sviryaev, Y., "Sleep stage classification based on bioradiolocation signals," in 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), August, 2015, pp. 362–365.
- [13] Kagawa, M., Tojima, H., & Matsui, T., "Non-contact diagnostic system for sleep apnea-hypopnea syndrome based on amplitude and phase analysis of thoracic and abdominal Doppler radars," *Medical & biological engineering & computing*, 2016, 54(5), 789–798.
- [14] Anishchenko, L., Zhuravlev, A., & Chizh, M., "Fall Detection Using Multiple Bioradars and Convolutional Neural Networks," *Sensors*, 2019, 19(24), 5569.
- [15] Radiofrequency electromagnetic radiation (RF EMR) under occupational and living conditions, SanPin 2.2.4/2.1.8.055-96, 1996.
- [16] Berry, R.B., Brooks, R., Gamaldo, C., Harding, S.M., Lloyd, R.M., Quan, S.F., Troester, M.T., Vaughn, B.V., "AASM scoring manual updates for 2017 (Version 2.4)," *J. Clin. Sleep. Med.*, 2017, 13(5), 665–666.