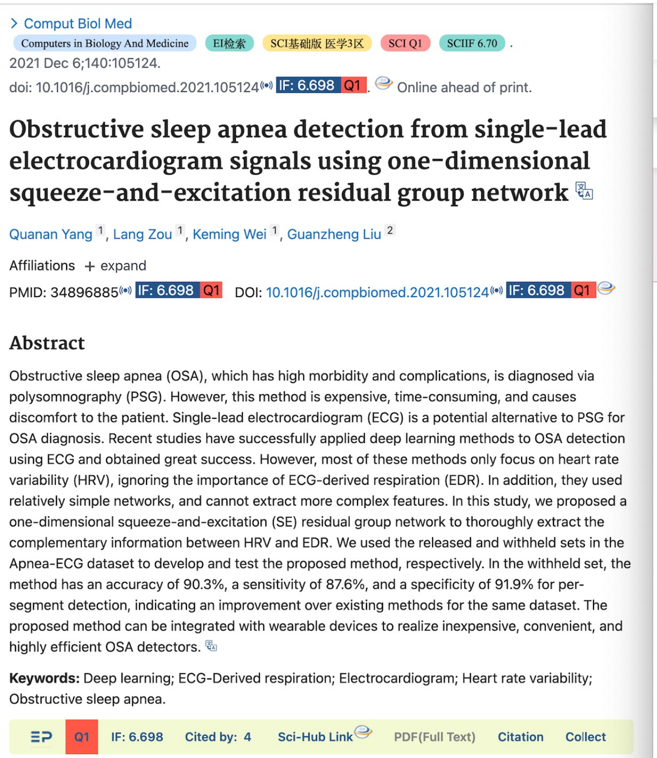
Technique Plan / Technique Feasibility Analysis

Q: Of the papers I shared with you, tell me the one that's most promising?

Answer: Thanks for the paper sharing. Among those shared papers, we have done some research to:

1. Check if there's any other good & similar tech papers using citation graph
2. Select well-known and high-quality papers using a filter [IF > 4.0 AND SCI-Q1 AND Connectivity > 3]



> Comput Biol Med
Computers in Biology And Medicine EI检索 SCI基础版 医学3区 SCI Q1 SCIIF 6.70 .
2021 Dec 6;140:105124.
doi: 10.1016/j.compbiomed.2021.105124 IF: 6.698 Q1 . Online ahead of print.

Obstructive sleep apnea detection from single-lead electrocardiogram signals using one-dimensional squeeze-and-excitation residual group network

Quanan Yang [1], Lang Zou [1], Keming Wei [1], Guanzheng Liu [2]

Affiliations + expand

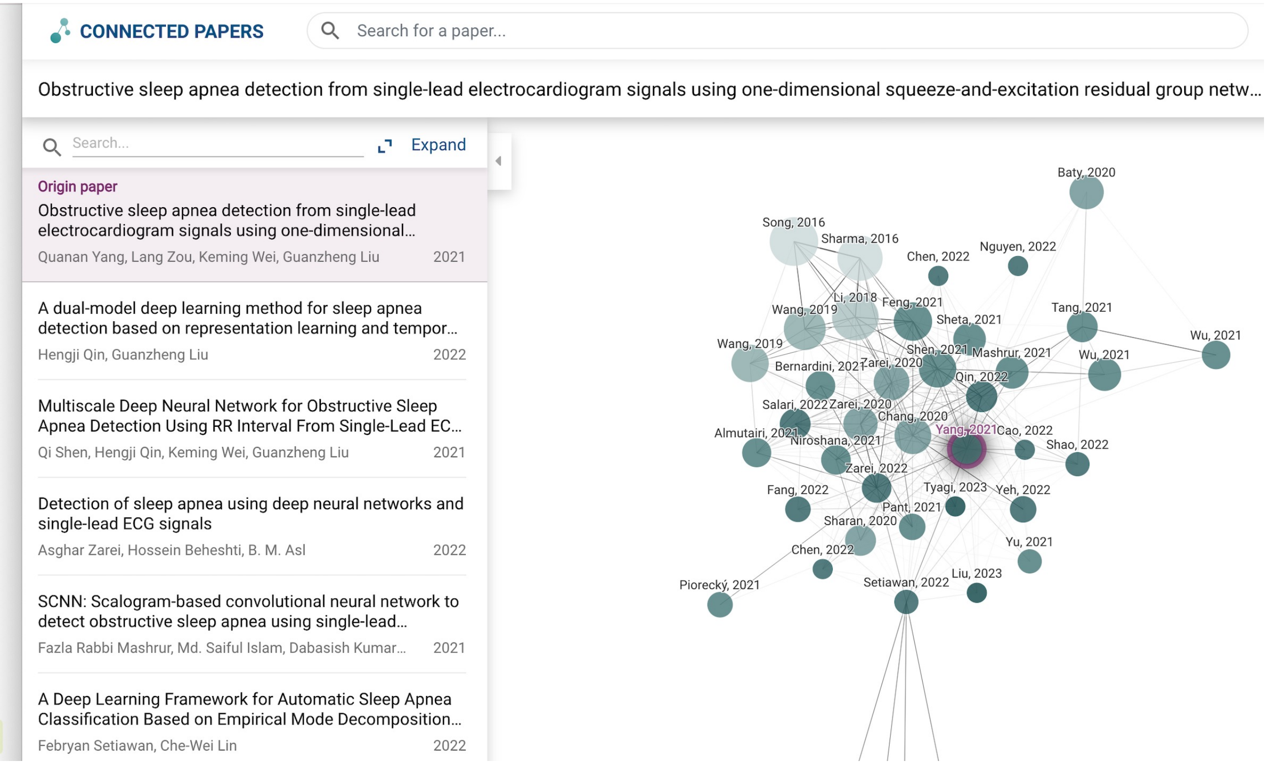
PMID: 34896885 IF: 6.698 Q1 DOI: 10.1016/j.compbiomed.2021.105124 IF: 6.698 Q1

Abstract

Obstructive sleep apnea (OSA), which has high morbidity and complications, is diagnosed via polysomnography (PSG). However, this method is expensive, time-consuming, and causes discomfort to the patient. Single-lead electrocardiogram (ECG) is a potential alternative to PSG for OSA diagnosis. Recent studies have successfully applied deep learning methods to OSA detection using ECG and obtained great success. However, most of these methods only focus on heart rate variability (HRV), ignoring the importance of ECG-derived respiration (EDR). In addition, they used relatively simple networks, and cannot extract more complex features. In this study, we proposed a one-dimensional squeeze-and-excitation (SE) residual group network to thoroughly extract the complementary information between HRV and EDR. We used the released and withheld sets in the Apnea-ECG dataset to develop and test the proposed method, respectively. In the withheld set, the method has an accuracy of 90.3%, a sensitivity of 87.6%, and a specificity of 91.9% for per-segment detection, indicating an improvement over existing methods for the same dataset. The proposed method can be integrated with wearable devices to realize inexpensive, convenient, and highly efficient OSA detectors.

Keywords: Deep learning; ECG-Derived respiration; Electrocardiogram; Heart rate variability; Obstructive sleep apnea.

Q1 IF: 6.698 Cited by: 4 Sci-Hub Link PDF(Full Text) Citation Collect



Technique Analysis (Landscape)

Among those shared papers (9), three of them has good quality:

A	B	C	D	E	F	G	H	I	J	K
Year	First Author	Paper full name	Journal / IF	No. citation	Database	Input signals	Algorithm	Evaluation method	Testing dataset	Key Result
~~2021~~	~~Mukherjee~~	~~Ensemble of Deep Learning Models for Sleep Apnea Detection: An Experimental Study~~	~~Sensors / 3.576~~	~~8~~	~~[Public] Apnea-ECG~~	~~Single Lead ECG~~	~~[Deep Learning] MLP, DNN, LSTM,~~	~~[Binary classification] Does one-minute ECG~~	~~Normal segment: 6100 (38.27%)~~	~~Sensitivity: 84.42% Specificity: 88.98%~~
~~2021~~	~~Liu~~	~~Comparison of Hospital-Based and Home-Based Obstructive Sleep Apnoea Severity Measurements with a Single-Lead Electrocardiogram Patch~~	~~Sensors / 3.576~~	~~2~~	~~Private~~	~~Single Lead ECG + 3-axes accelerometer~~	-	~~The study compares sleep index between hospital and home setting by using~~	~~no-to-mild (AHI < 15): 24 (23.30%) moderate (15 <= AHI < 30): 24~~	~~The results indicate that patients may spend a higher percentage of sleep~~
~~2021~~	~~Yang~~	~~Obstructive sleep apnea detection from single-lead electrocardiogram signals using one-dimensional squeeze-~~								
~~2022~~	~~Yeh~~	~~Contribution of Different Subbands of ECG in Sleep Apnea Detection Evaluated Using Filter Bank Decomposition and a~~	~~Sensors / 3.576~~	~~3~~	~~[Public] Apnea-ECG~~	~~Single Lead ECG~~	~~[Deep Learning] filter bank, CNN~~	~~[Binary classification] Does one-minute ECG~~	~~Normal segment: 10586 (61.31%)~~	~~Sensitivity: 79.0% Specificity: 90.2%~~
~~2022~~	~~Romero~~	~~Detecting Obstructive Apnea Episodes using Dynamic Bayesian Networks and ECG-based Time-Series~~	~~IEEE EMBC~~	~~0~~	~~Private~~	~~Single Lead ECG~~	~~[Machine Learning]~~	~~[Binary classification] Does 15-seconds ECG~~	~~Unclear~~	~~Sensitivity: 90.0% Specificity: 78.0%~~
~~2022~~	~~Indrawati~~	~~Obstructive Sleep Apnea Detection using Frequency Analysis of Electrocardiographic RR Interval and Machine Learning~~	~~Journal of Biomedical Physics~~	~~0~~	~~[Public] Apnea-ECG~~	~~Single Lead ECG~~	~~[Deep Learning] ANN~~	~~[Binary classification] Does one-minute ECG~~	~~Unclear~~	~~Sensitivity: 94.21% Specificity: 64.03%~~
2023	Yue	Validity study of a multi-scaled fusion network using single-lead electrocardiogram signals for obstructive sleep apnea	American Academy of Sleep	0	TBD	TBD	TBD	TBD	TBD	TBD
2020	Zarei	Obstructive sleep apnea detection from single-lead electrocardiogram signals using one-dimensional squeeze-	computer methods and programs in	26	[Public] Apnea-ECG	Single Lead ECG	[Machine Learning] feature	[Binary classification] Is one-night ECG	70 records from 32 subjects. Some of	Accuracy: 97.14%
2018	Li	A Method to Detect Sleep Apnea based on Deep Neural Network and Hidden Markov Model using Single-Lead ECG	Neurocomputing / 5.719	140	[Public] Apnea-ECG	Single Lead ECG	[Deep Learning, Machine	[Binary classification] Is one-night ECG	AHI < 5 record: 12 (48%)	Sensitivity: 100%, Specificity: 100%

Technique Analysis (Pitfalls and Conclusion)

There are at least 4-5 similar papers can be found [1-4]. Many of them use deep learning and single-lead EKG for OSA detection, and they can reach 88%-95% overall accuracy on binary classifications.

However, there are pitfalls in their validation process i.e. The hold-out validation strategy shall be built on patient ID (patient 1-10 for training, and patient 11-20 for validation) rather than signal-segment ID. After fixing this pitfall, some papers accuracy reduces at least 8%. Therefore, we estimate the real-world ECG deep learning method can reach 79%-87%.

(Traditional machine learning papers [5] also can reach a good performance/looks competitive. But similar pitfalls found in their validation process)

Conclusion:

(1) There are 6 papers/techs identified as promising => Please see highlights in page 3 and 4

(2) There are pitfalls in validation process. Real-world performance could be 79%-88% for OSA binary classification.

[1] Qin, et al. "A dual-model deep learning method for sleep apnea detection based on representation learning and temporal dependence." *Neurocomputing* 473 (2022): 24-36.
[2] Mashrur, et al. "SCNN: Scalogram-based convolutional neural network to detect obstructive sleep apnea using single-lead electrocardiogram signals." *Computers in Biology and Medicine* 134 (2021): 104532.
[3] Shen, et al. "Multiscale deep neural network for obstructive sleep apnea detection using RR interval from single-lead ECG signal." *IEEE Transactions on Instrumentation and Measurement* 70 (2021): 1-13.
[4] Zarei, at al. "Automatic classification of apnea and normal subjects using new features extracted from HRV and ECG-derived respiration signals." *Biomedical Signal Processing and Control* 59 (2020): 101927.
[5] Salari, et al. "Detection of sleep apnea using Machine learning algorithms based on ECG Signals: A comprehensive systematic review." *Expert Systems with Applications* 187 (2022): 115950.

biofourmis

Appendix: Apnea ECG dataset pitfall

Apnea ECG dataset was release in 2000 for a challenge by Physionet. There are 35 records for training and 35 records for testing which they were withheld at that time.

The withheld record names are x01, x02, … to x35 while the training record names start with a, b or c.

After the challenge ended, the withheld records were released, and they are 70 records in total.

A lot of publications follow train-test split by the challenge describe above. In short, they use the withheld records x01-x35 as a test set.

However, all 70 records came from only 32 subjects, meaning that some of the withheld records came from the subjects that their records are also in the train set.

Therefore, a lot of result published are not subject-independent. This issue is dangerous and can give a wrong impression at first glance since generally the detail of train-test splitting is not written in abstract.

Subject No.	ECG Recording No.			
@p1	a01	a14		
p2 *	a02	x14 +		
@p3 *	a03	x19 +		
@p4	a04	a12		
p5 *	a05	a10	a20	x07 +
@p6 *	a06	x15+		
@p7 *	a07	a16	x01 +	x30 +
p8 *	a08	a13	x20 +	
p9	a09	a18		
@p10	a11			
@p11 *	a15	x27 +	x28 +	
@p12 *	a17	x12 +		
p13 *	a19	x05 +	x08 +	x25 +
@p14 *	b01	x03 +		
p15*	b02	b03	x16 +	x21 +
p16	b04	c08		

Subject No.	ECG Recording No.	
@p17 *	b05	x11 +
p18 *	c01	x35 +
@p19	c02	c09
p20 *	c03	x04 +
@p21 *	c04	x29 +
p22 *	c05	x33 +
@p23	c06	
@p24 *	c07	x34 +
@p25 *	c10	x18 +
p26	x02	
@p27	x06	x24
@p28	x09	x23
P29	x10	
p30	x13	x26
p31	x17	x22
p32	x31	x32