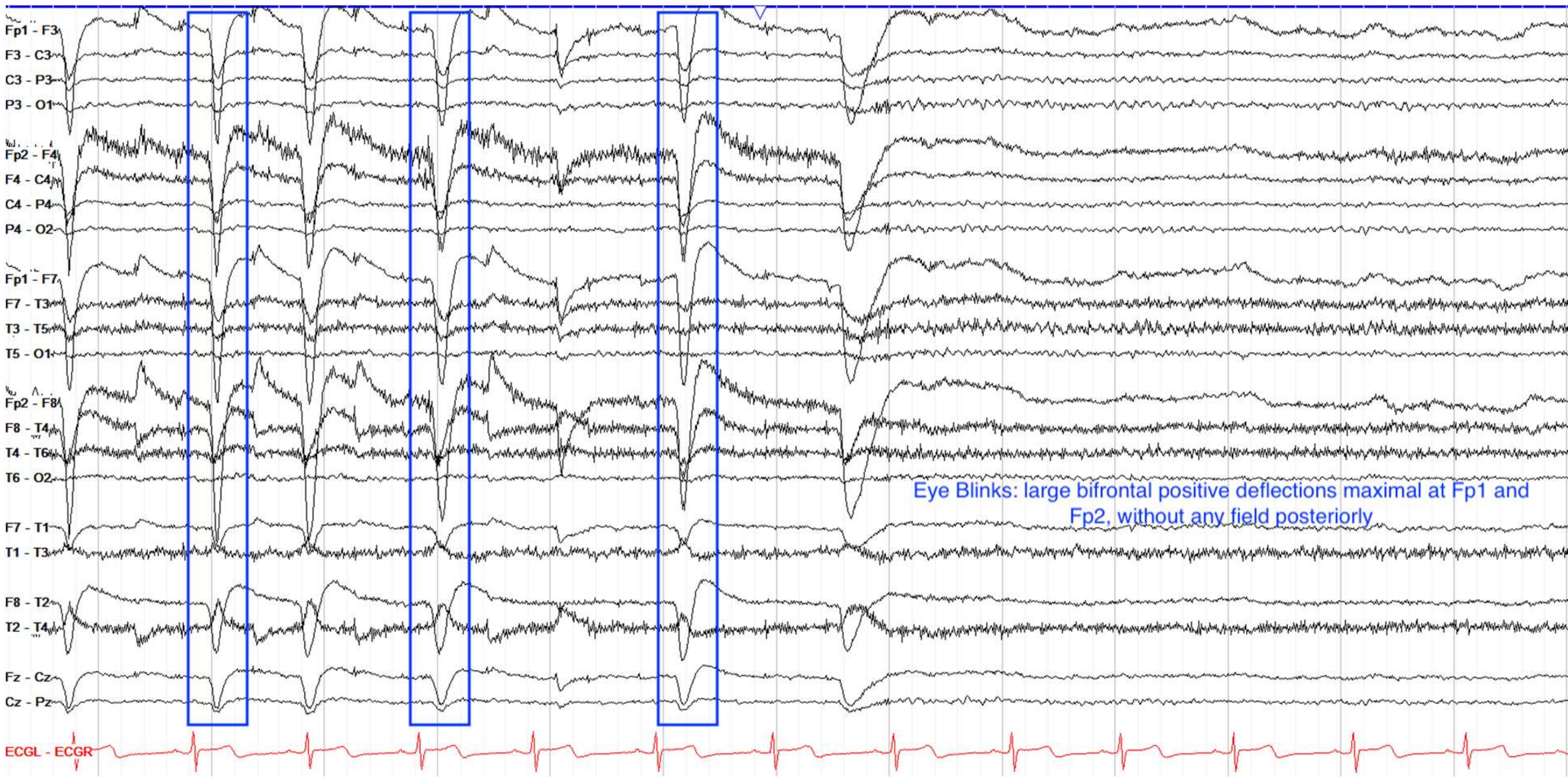
EEG denoising

Problem

- Removing artifacts from EEG signals with minimum distortion and contamination
  - enhance the BCI performance
  - increase the accuracy of data interpretation
  - enhance classification models performance

Types of artifacts

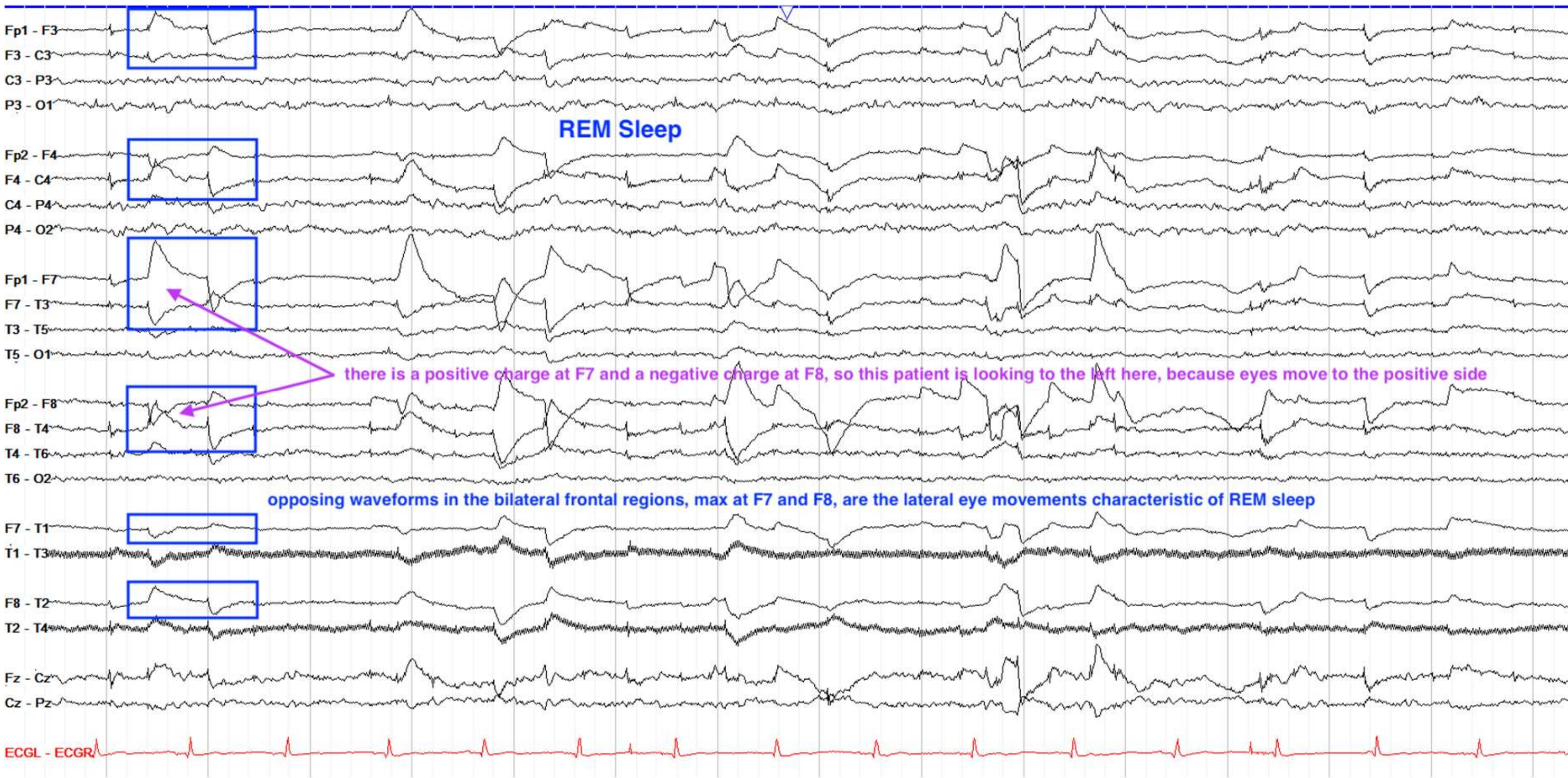
- Eye blinks



https://www.learningeeg.com/artifacts

Types of artifacts

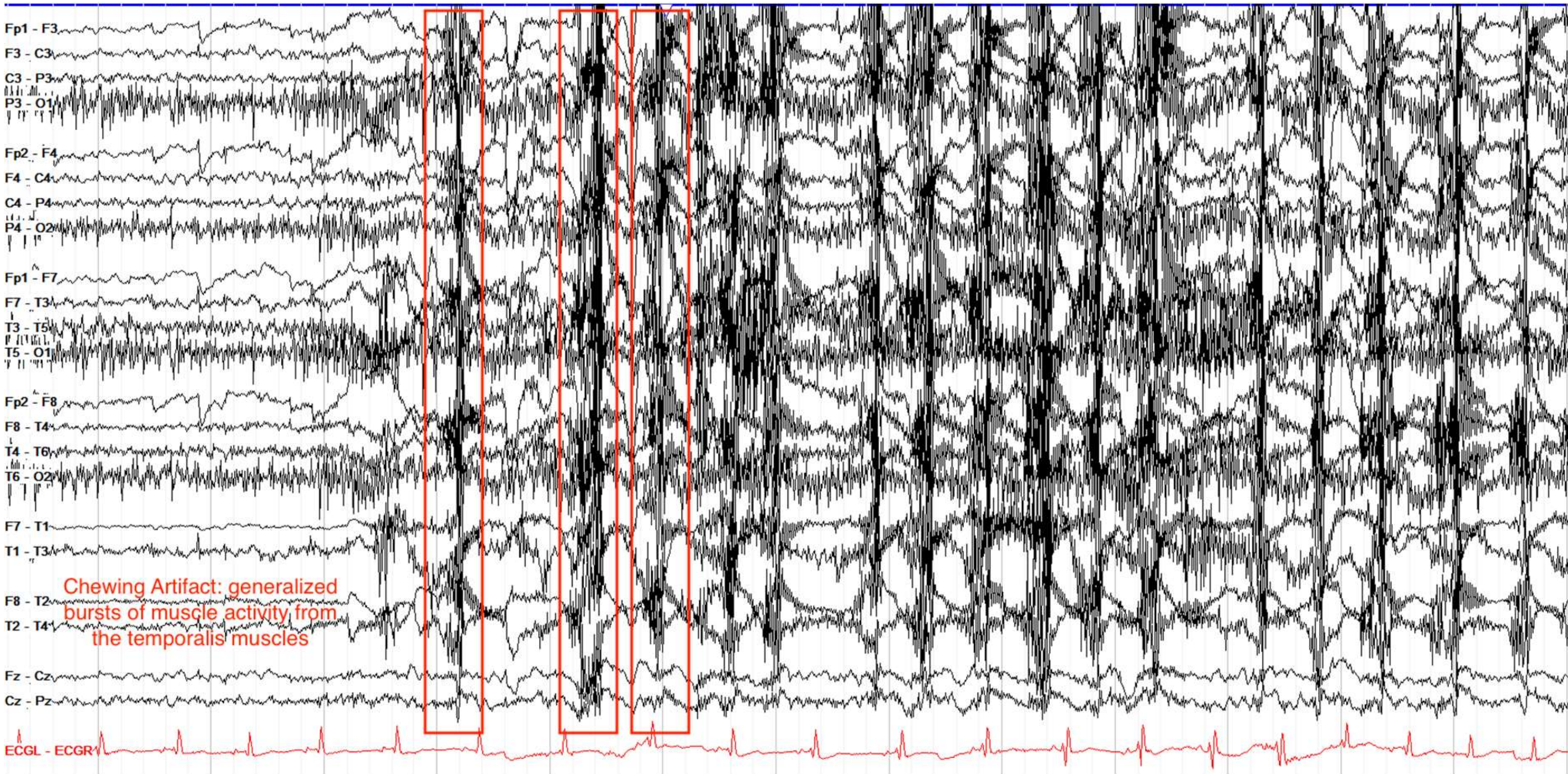
- Eye blinks
- Lateral eye movements



https://www.learningeeg.com/artifacts

Types of artifacts

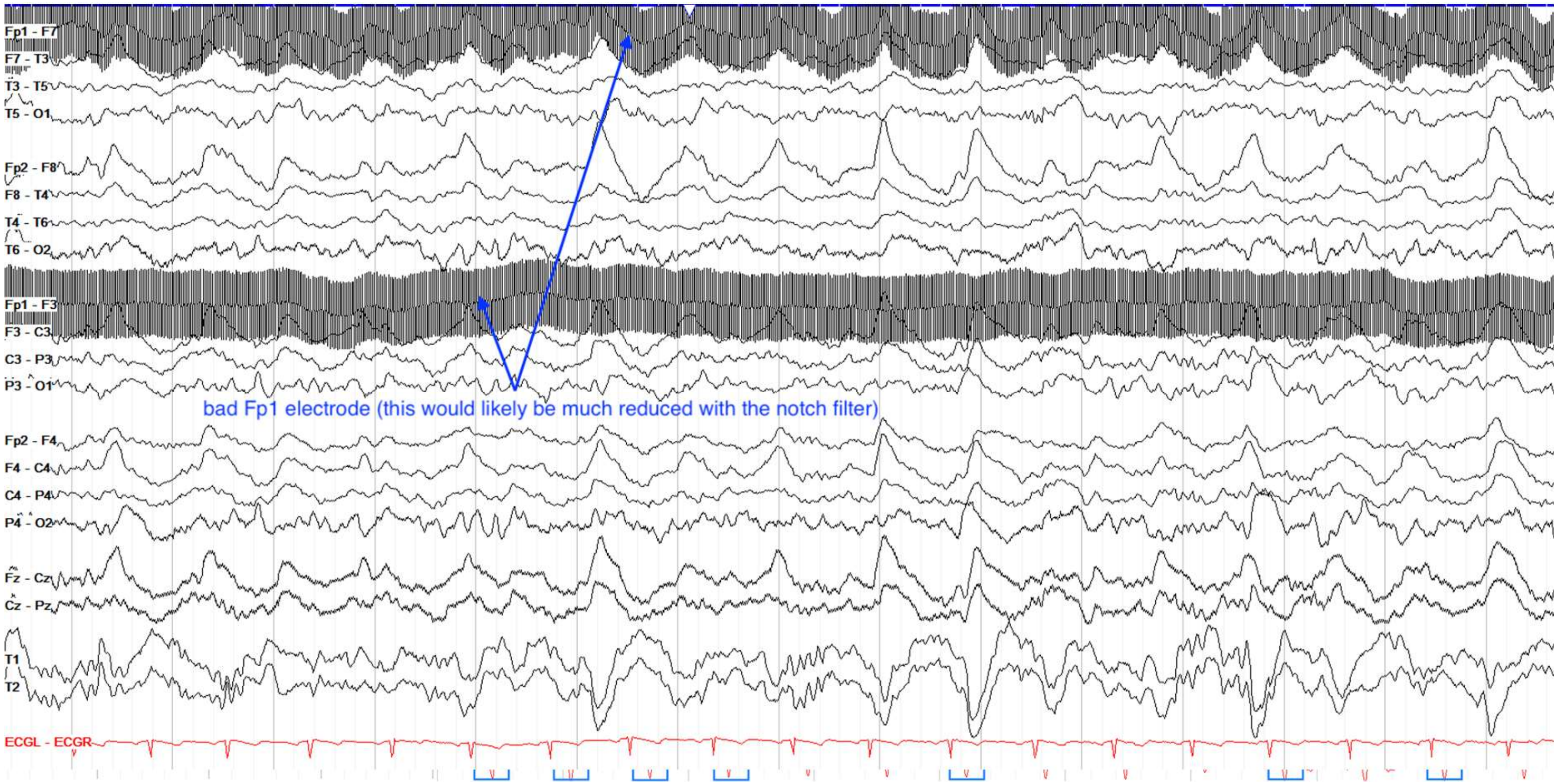
- Eye blinks
- Lateral eye movements
- Chewing and tongue artifact



https://www.learningeeg.com/artifacts

Types of artifacts

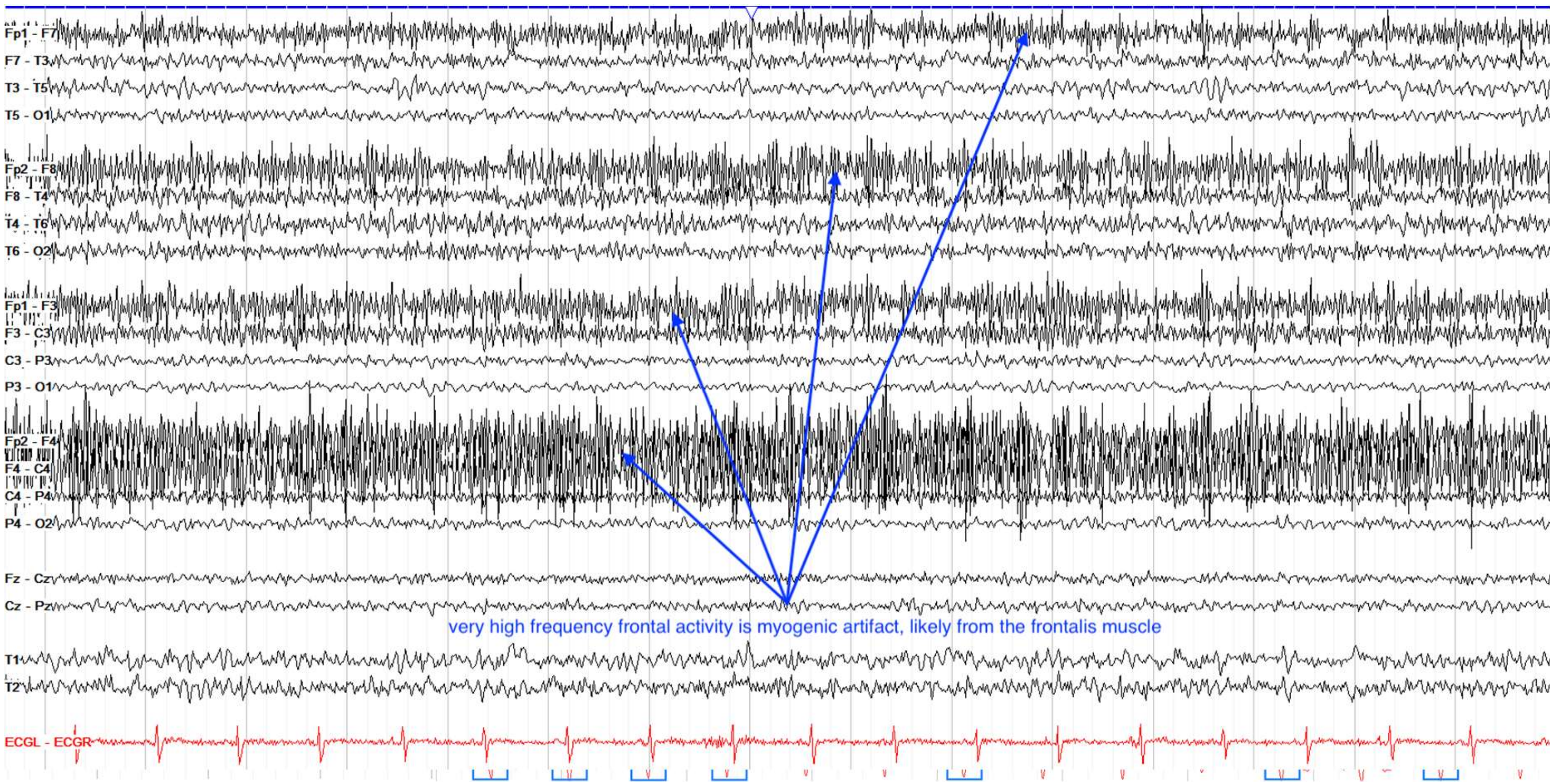
- Eye blinks
- Lateral eye movements
- Chewing and tongue artifact
- ECG artifact
- Electrical artifact



https://www.learningeeg.com/artifacts

Types of artifacts

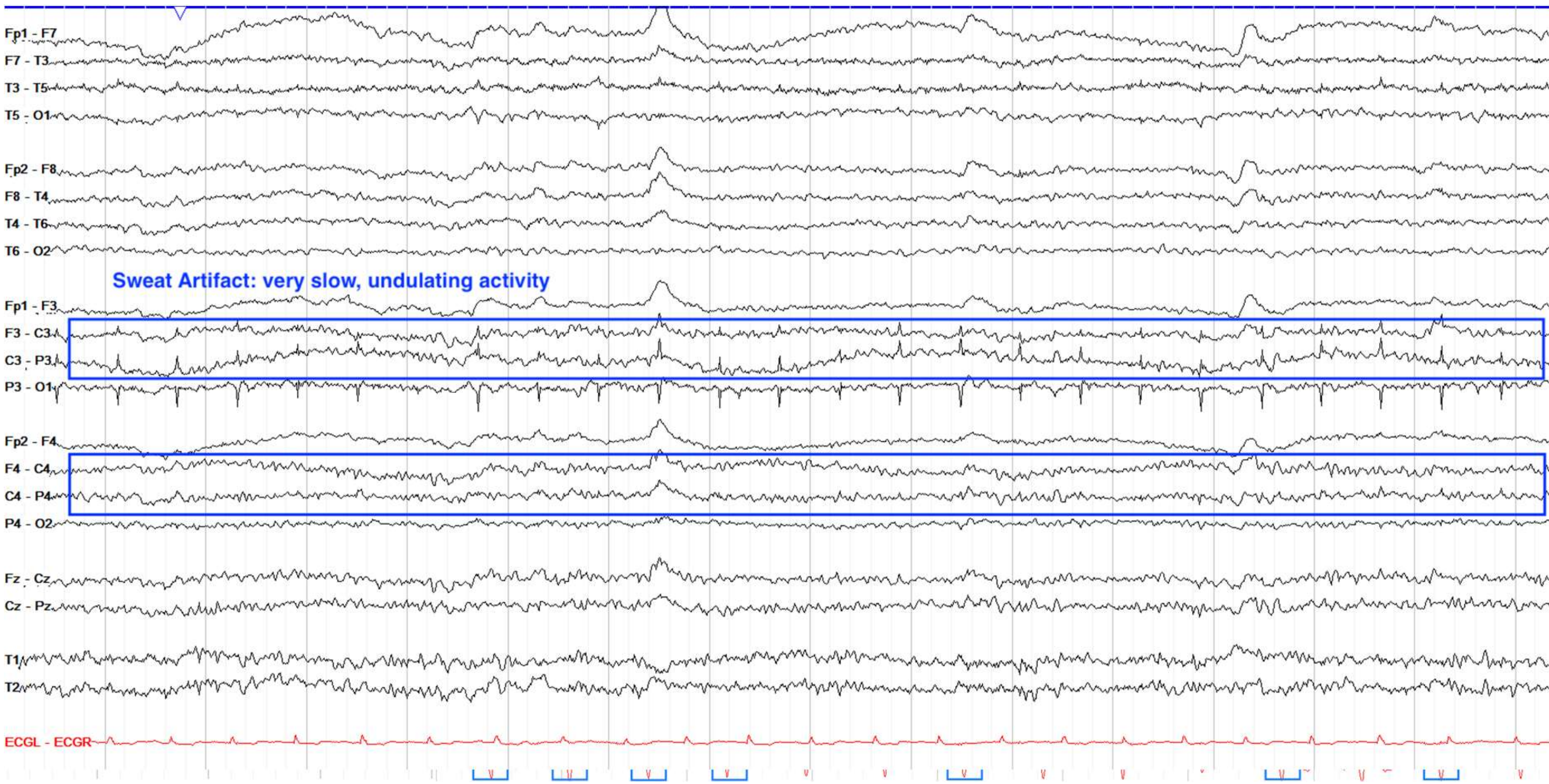
- Eye blinks
- Lateral eye movements
- Chewing and tongue artifact
- ECG artifact
- Electrical artifact
- Myogenic artifact



https://www.learningeeg.com/artifacts

Types of artifacts

- Eye blinks
- Lateral eye movements
- Chewing and tongue
- ECG
- Electrical
- Myogenic
- Sweat



https://www.learningeeg.com/artifacts

Approaches

Blind source separation (BSS) methods

- Artifact subspace reconstruction (ASR)
- Independent component analysis (ICA)

ML/DL

- Residual CNN
- Autoencoder
- UNet
- GAN
- Transfomer

Approaches

Blind source separation (BSS) methods

- Artifact subspace reconstruction (ASR)
- Independent component analysis (ICA)

ML/DL

- Residual CNN
- Autoencoder
- UNet
- GAN
- Transfomer

- Use statistical assumptions
- Single nonlinear/linear mapping function, might be too simplistic
- Not fully automated

Deep Convolutional Autoencoder (DAE)

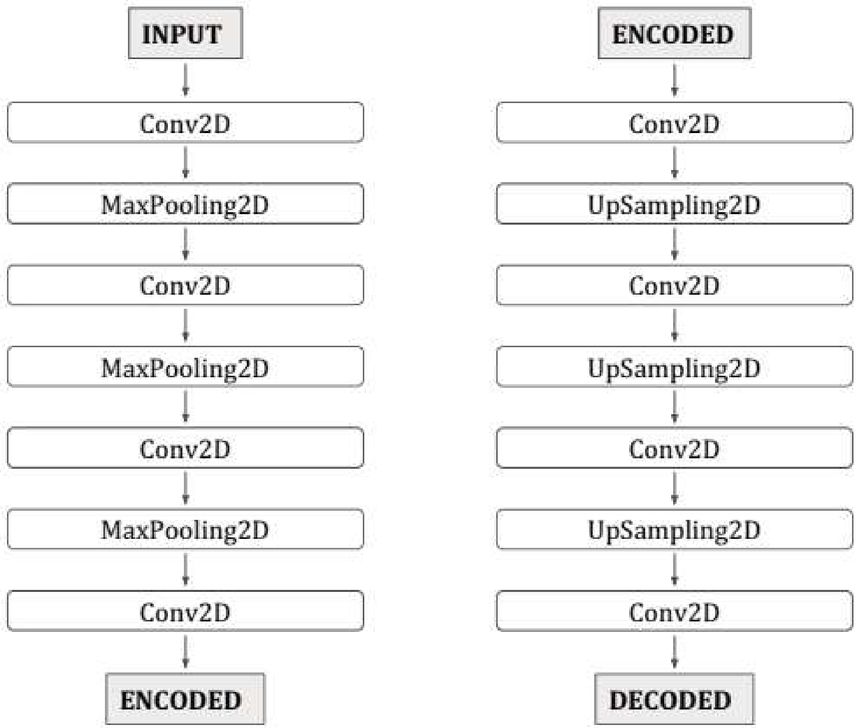


Fig. 2. Architecture developed to tackle the proposed problem.

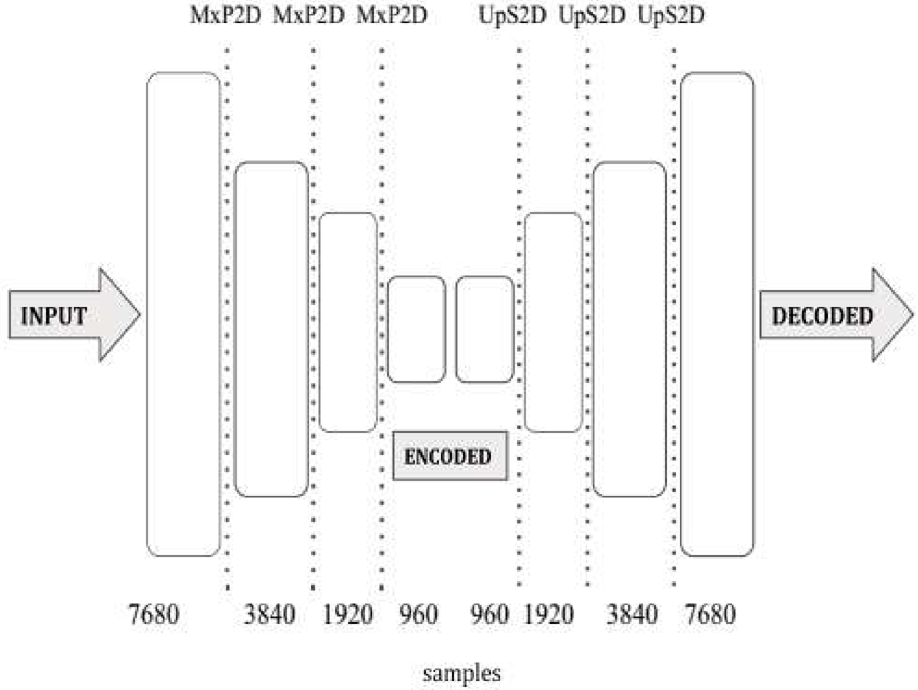


Fig. 3. Dimensionality analysis of the autoencoder. MxP2D and UpS2D are MaxPooling2D and UpSampling2D layers, respectively.

F. Lopes *et al.*, "Automatic Electroencephalogram Artifact Removal Using Deep Convolutional Neural Networks," in *IEEE Access*, vol. 9, pp. 149955-149970, 2021, doi: 10.1109/ACCESS.2021.3125728.

Deep Convolutional Autoencoder (DAE)

- Data
  - 19 channels
  - 128 Hz
  - chunk length 7680 (60 s)
  - normalization

F. Lopes *et al*., "Automatic Electroencephalogram Artifact Removal Using Deep Convolutional Neural Networks," in *IEEE Access*, vol. 9, pp. 149955-149970, 2021, doi: 10.1109/ACCESS.2021.3125728.

Deep Convolutional Autoencoder (DAE)

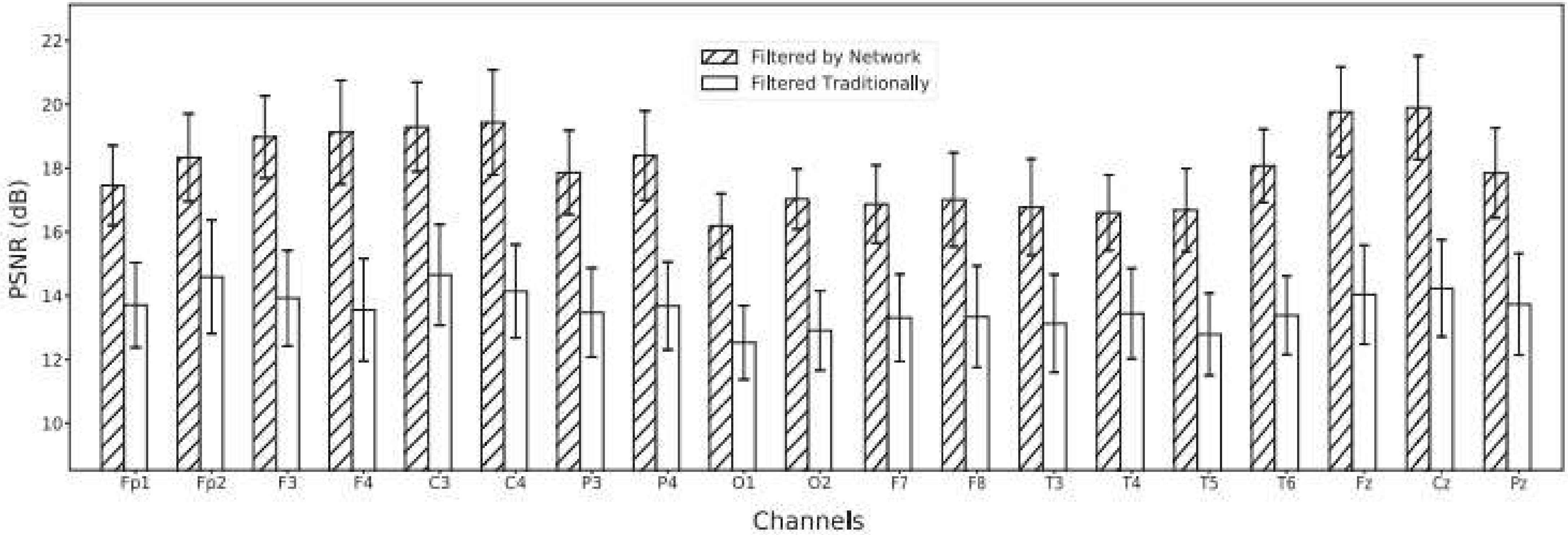


Fig. 9. Confidence intervals of the average PSNR for blink noise.

F. Lopes *et al*., "Automatic Electroencephalogram Artifact Removal Using Deep Convolutional Neural Networks," in *IEEE Access*, vol. 9, pp. 149955-149970, 2021, doi: 10.1109/ACCESS.2021.3125728.

Deep Convolutional Autoencoder (DAE)

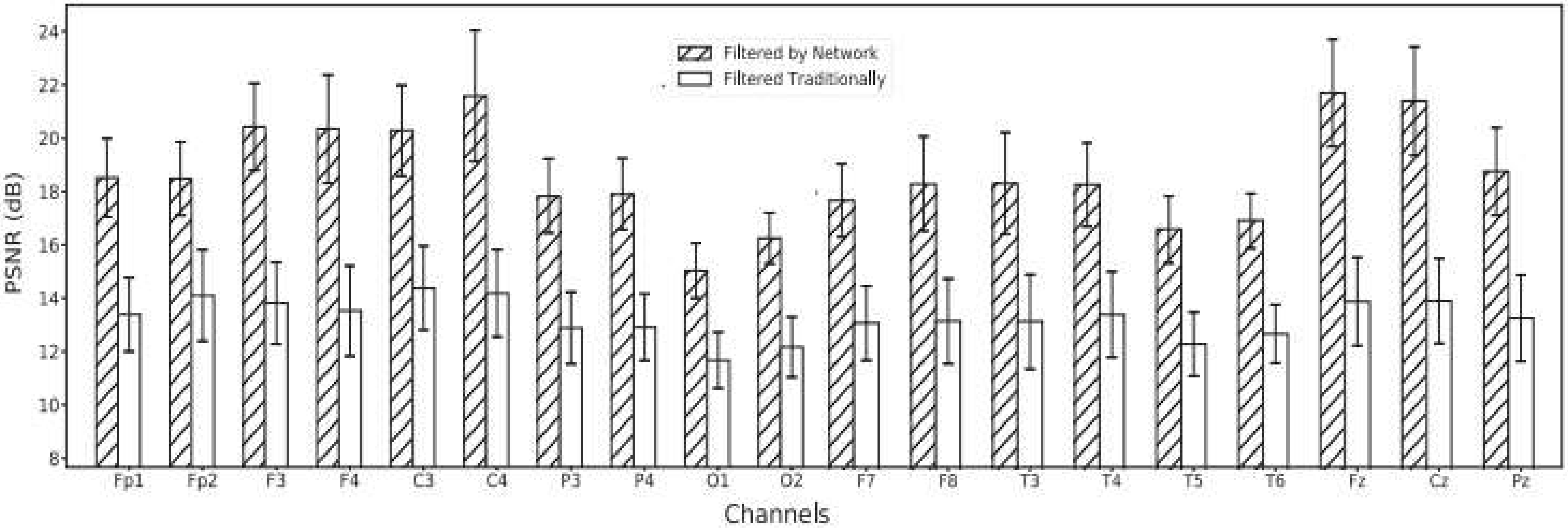
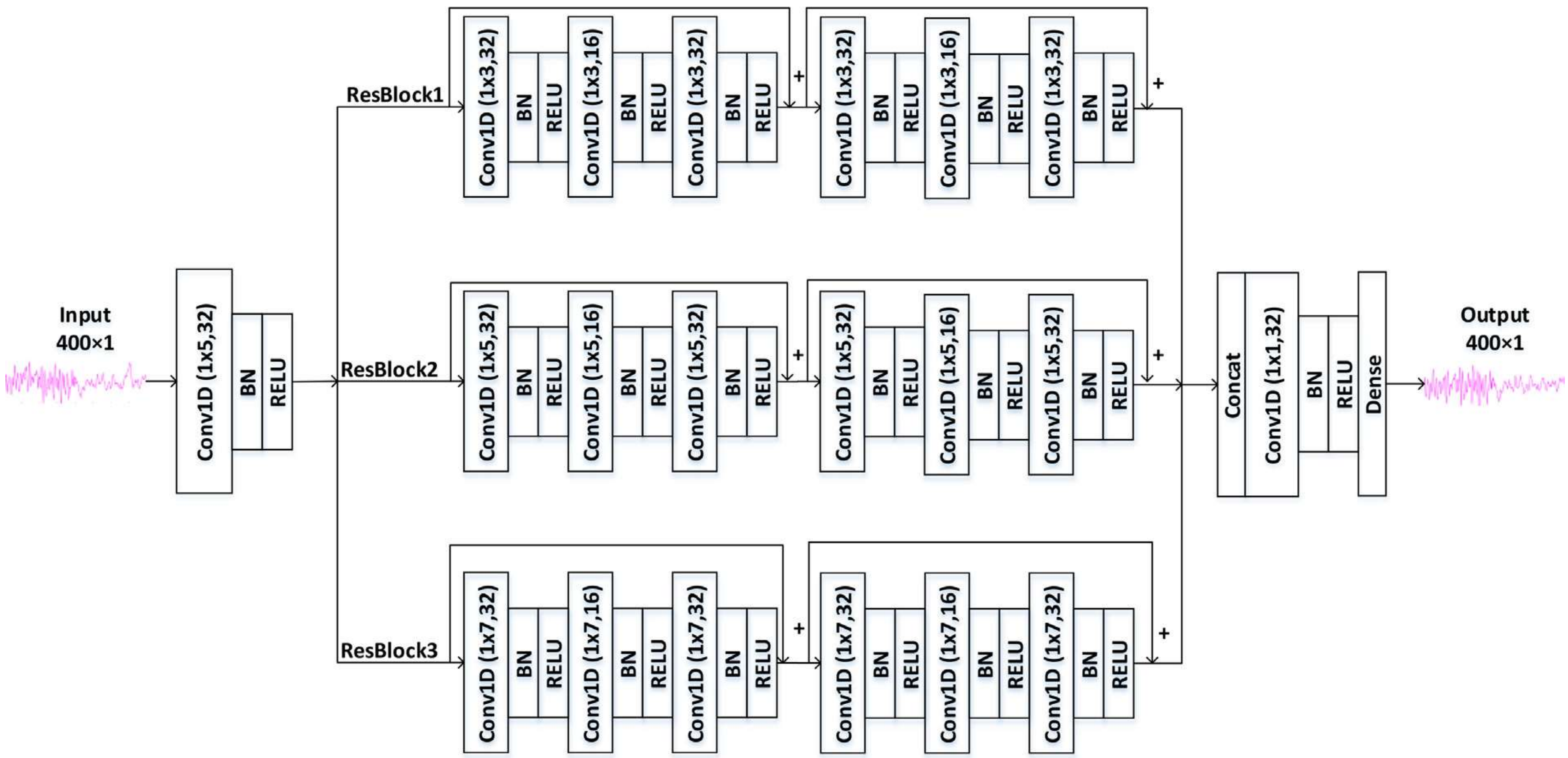


Fig. 10. Confidence intervals of the average PSNR for jaw clenching noise.

F. Lopes *et al*., "Automatic Electroencephalogram Artifact Removal Using Deep Convolutional Neural Networks," in *IEEE Access*, vol. 9, pp. 149955-149970, 2021, doi: 10.1109/ACCESS.2021.3125728.

1D-ResCNN



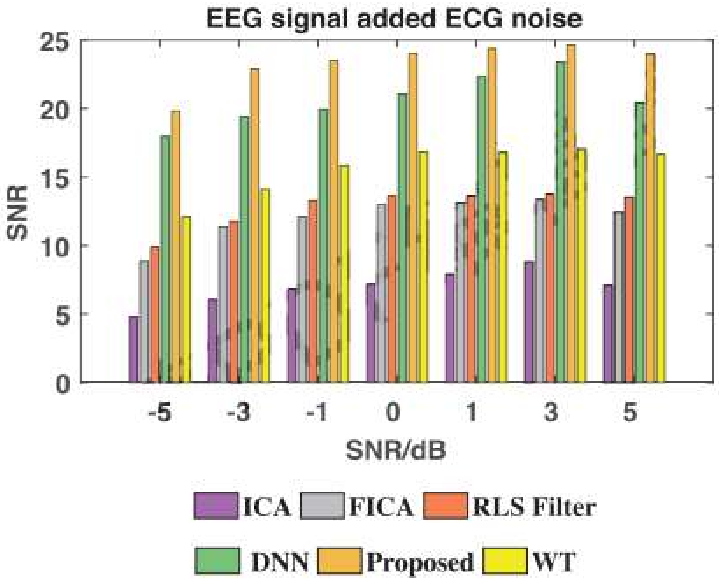
Sun, W., Su, Y., Wu, X., Wu, X., 2020. A novel end-to-end 1D-ResCNN model to remove artifact from EEG signals. Neurocomputing 404, 108–121.

1D-ResCNN

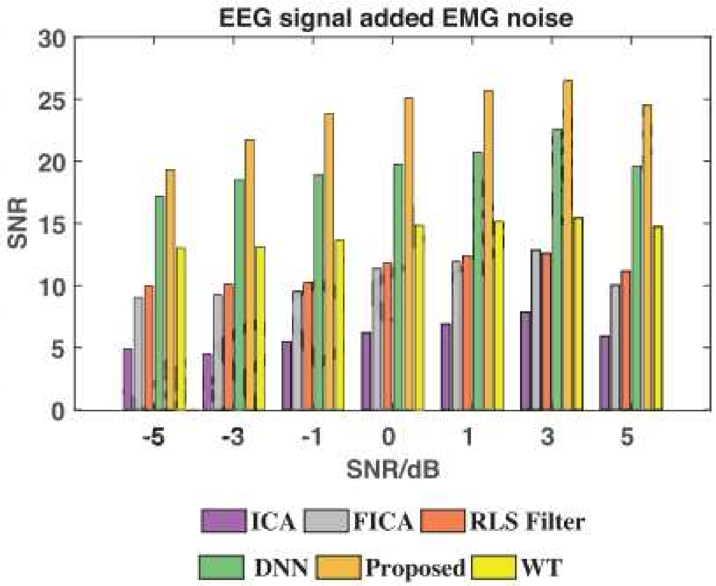
- Data
  - 256 Hz
  - window size of 400, stride 380 (~1.56 s)
  - normalization

Sun, W., Su, Y., Wu, X., Wu, X., 2020. A novel end-to-end 1D-ResCNN model to remove artifact from EEG signals. Neurocomputing 404, 108–121.

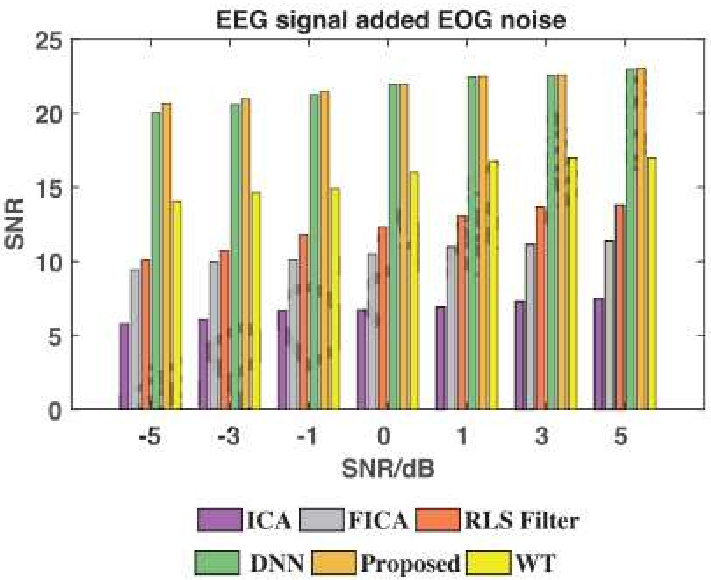
1D-ResCNN



(a) SNR results of remove ECG noise from EEG signal



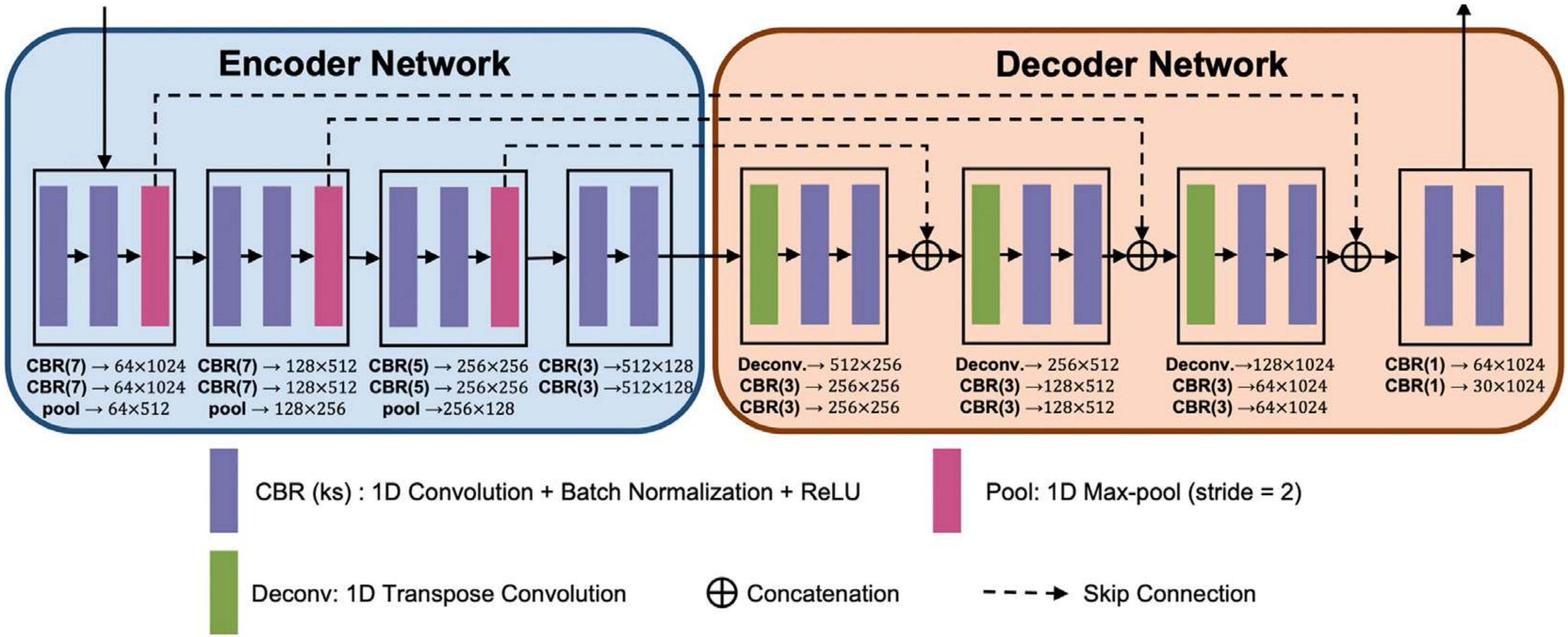
(b) SNR results of remove EMG noise from EEG signal



(c) SNR results of remove EOG noise from EEG signal

Sun, W., Su, Y., Wu, X., Wu, X., 2020. A novel end-to-end 1D-ResCNN model to remove artifact from EEG signals. Neurocomputing 404, 108–121.

IC-U-Net



Chun-Hsiang Chuang, Kong-Yi Chang, Chih-Sheng Huang, Tzyy-Ping Jung, IC-U-Net: A U-Net-based Denoising Autoencoder Using Mixtures of Independent Components for Automatic EEG Artifact Removal, NeuroImage, Volume 263, 2022, 119586, ISSN 1053-8119,

IC-U-Net

- Data
  - 30 channels
  - 256 Hz
  - chunk length 1024 (4 s)
  - normalization

Chun-Hsiang Chuang, Kong-Yi Chang, Chih-Sheng Huang, Tzyy-Ping Jung, IC-U-Net: A U-Net-based Denoising Autoencoder Using Mixtures of Independent Components for Automatic EEG Artifact Removal, NeuroImage, Volume 263, 2022, 119586, ISSN 1053-8119,

IC-U-Net

- Results

Performance comparison of the proposed method and three other methods

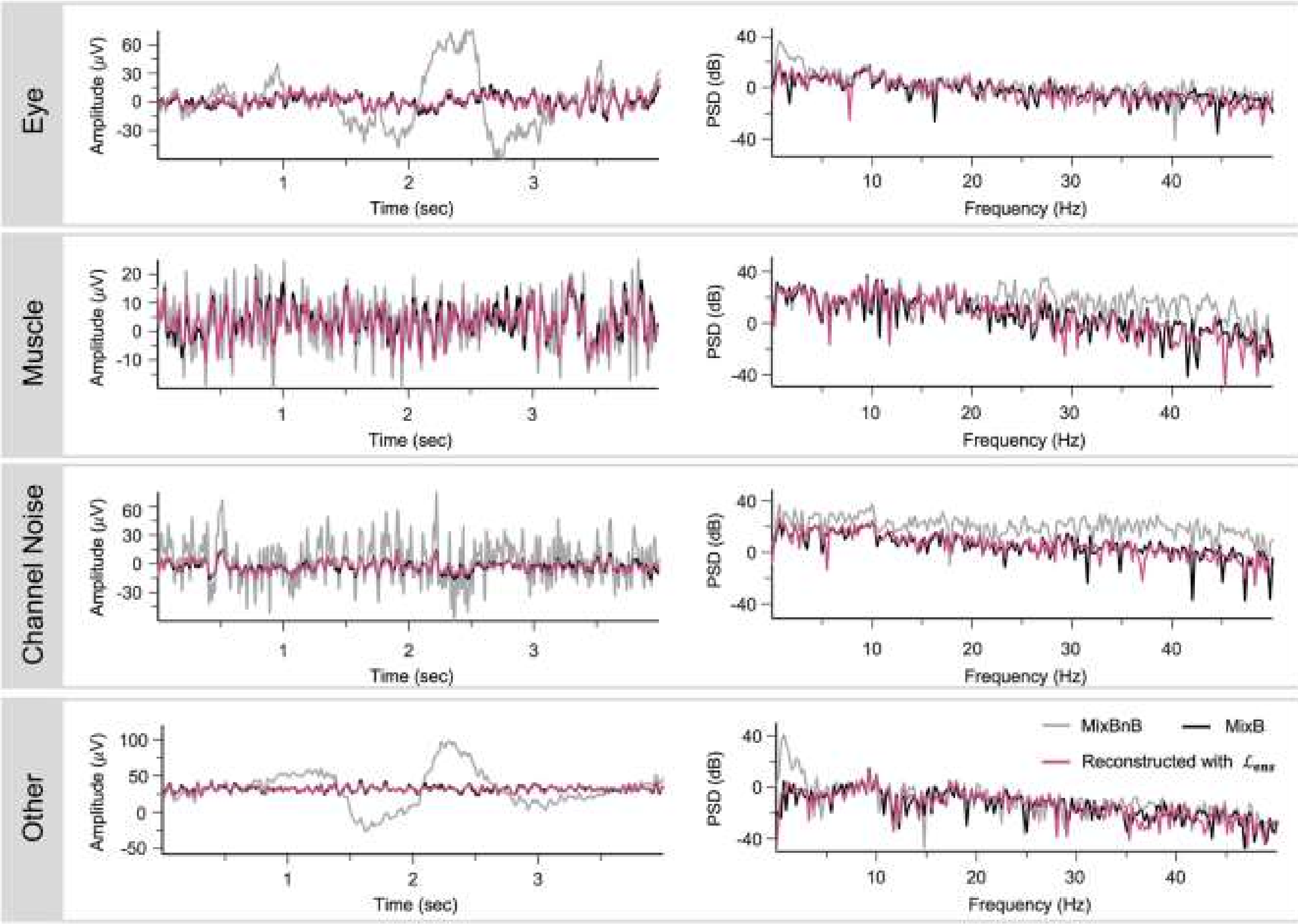
		Artifact					
Dataset	Number Method	Eye 171 MSE	Muscle 273	Other 273	Eye 171 SNR	Muscle 273	Other 273
Lane-keeping driving datasets	Filter	1.81 ± 1.08	1.74 ± 0.74	1.63 ± 0.78	−2.25 ± 2.97	−2.52 ± 3.37	−2.14 ± 3.32
	ASR	1.44 ± 0.98	1.40 ± 0.89	1.44 ± 0.99	−1.06 ± 3.51	−1.29 ± 3.58	−1.36 ± 3.12
	1D-ResCNN	1.42 ± 0.94	2.12 ± 0.93	1.42 ± 0.73	−0.98 ± 2.66	−3.31 ± 3.24	−1.43 ± 2.64
	IC-U-Net	**0.57** ± 0.58	**0.56** ± 0.51	**0.87** ± 0.55	**4.06** ± 3.56	**3.62** ± 3.09	± 3.34

Heart, Line Noise, and Channel Noise were omitted because they were rarely decomposed from this dataset.

Chun-Hsiang Chuang, Kong-Yi Chang, Chih-Sheng Huang, Tzyy-Ping Jung, IC-U-Net: A U-Net-based Denoising Autoencoder Using Mixtures of Independent Components for Automatic EEG Artifact Removal, NeuroImage, Volume 263, 2022, 119586, ISSN 1053-8119,

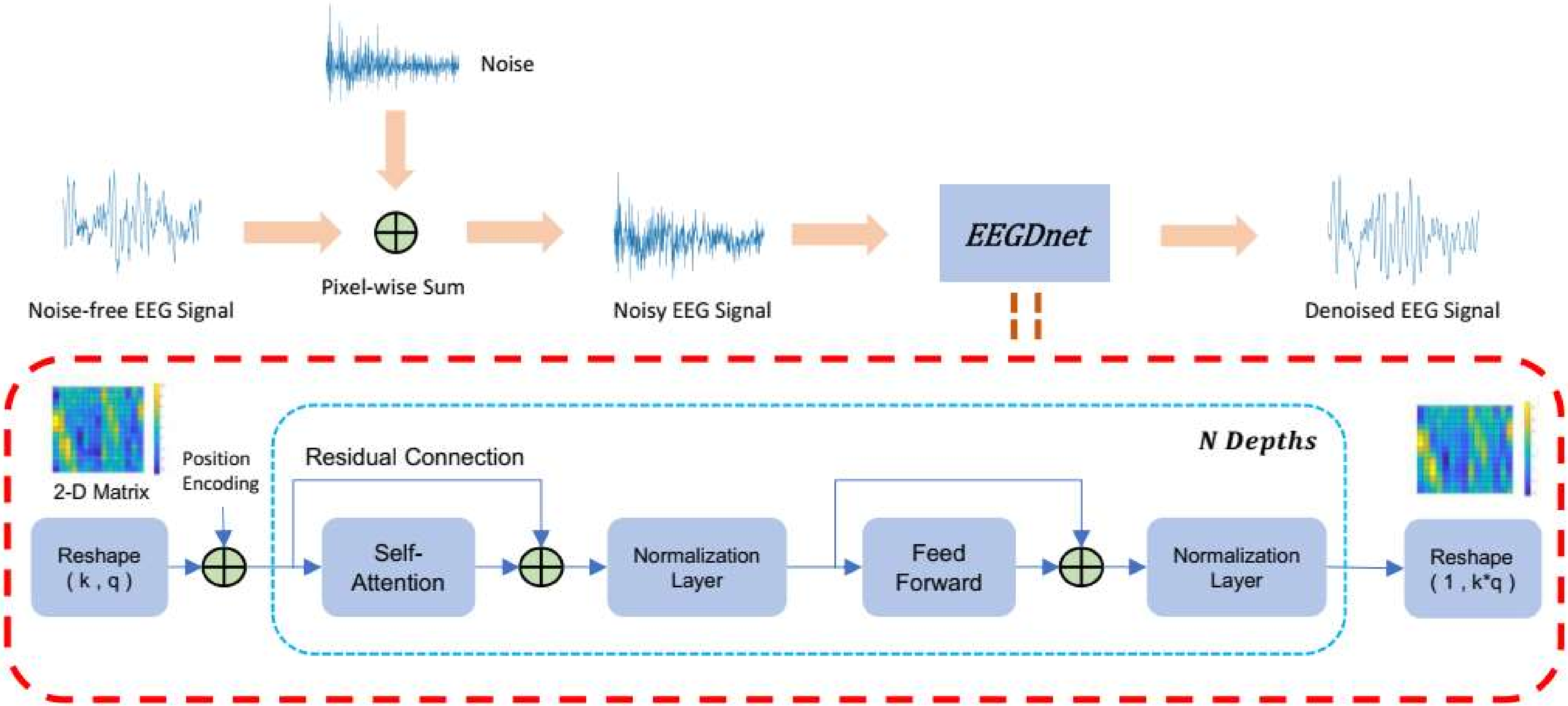
IC-U-Net

- Results



Chun-Hsiang Chuang, Kong-Yi Chang, Chih-Sheng Huang, Tzyy-Ping Jung, IC-U-Net: A U-Net-based Denoising Autoencoder Using Mixtures of Independent Components for Automatic EEG Artifact Removal, NeuroImage, Volume 263, 2022, 119586, ISSN 1053-8119,

EEGDnet transformer



Yi, Peng & Chen, Kecheng & Ma, Zhaoqi & Zhao, Di & Pu, Xiaorong & Ren, Yazhou. (2021). EEGDnet: Fusing Non-Local and Local Self-Similarity for 1-D EEG Signal Denoising with 2-D Transformer.

EEGDnet transformer

- Data
  - EEGDnet dataset
  - No channels
  - 256 Hz
  - epoch length 512 (2 seconds)
  - 4514 EEG epochs
  - 3400 ocular artifact epochs
  - 5598 muscle artifact epochs
  - Mixed signals are generated via $y = x + \lambda n$ with a uniformly distributed SNR from -7dB to 2d (x10 to dataset size)

Yi, Peng & Chen, Kecheng & Ma, Zhaoqi & Zhao, Di & Pu, Xiaorong & Ren, Yazhou. (2021). EEGDnet: Fusing Non-Local and Local Self-Similarity for 1-D EEG Signal Denoising with 2-D Transformer.

EEGDnet transformer

Table 1: Average performances of all SNRs (from -7dB to 2dB). The smaller $RRMSE_{temporal}$ and $RRMSE_{spectral}$, and the larger CC, the better denoising effect. The baseline of EEGDnet consists of 6 $Depths$ and 1 $Head$ with $k \times q$ equals to 8×64. Note that all the models are trained and tested on the same data set. For $RRMSE_{temporal}$, $RRMSE_{spectral}$, the lower the better. For CC, the higher the better. The best result is shown in bold.

Model	Self-Similarity		Ocular Artifact			Muscle Artifact		
	local	non-local	$RRMSE_{temporal}$	$RRMSE_{spectral}$	CC	$RRMSE_{temporal}$	$RRMSE_{spectral}$	CC
DLN (Yang et al. 2018)		✓	0.699	0.579	0.720	0.917	1.081	0.609
SCNN (Zhang et al. 2020)	✓		0.620	0.526	0.791	0.750	0.697	0.706
1D-ResCNN (Sun et al. 2020)	✓		0.630	0.588	0.776	0.746	0.680	0.692
RNN (Zhang et al. 2020)		✓	0.740	0.696	0.677	0.785	0.775	0.636
EEGDnet	✓	✓	**0.497**	**0.491**	**0.868**	**0.677**	**0.626**	**0.732**

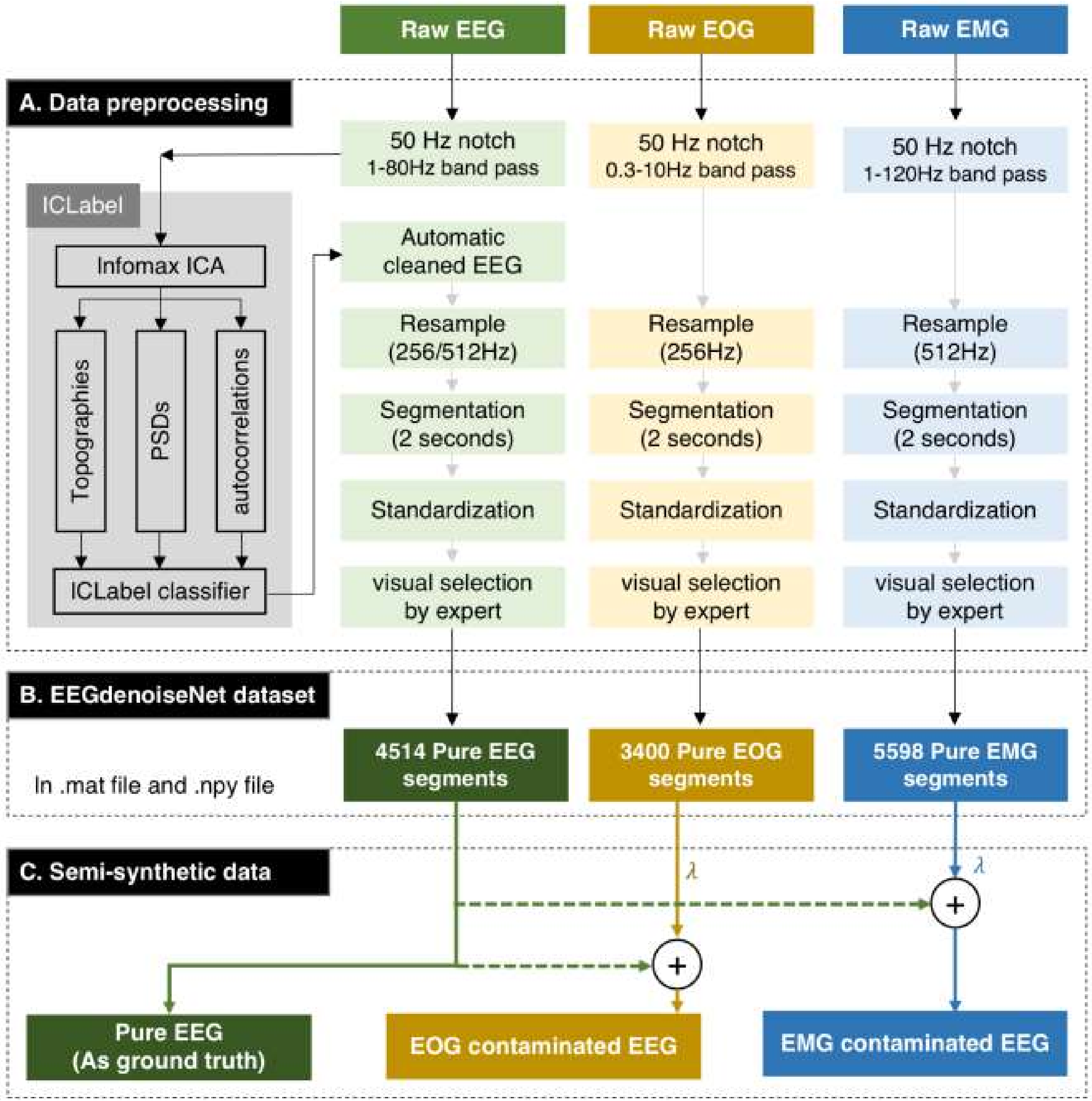
Yi, Peng & Chen, Kecheng & Ma, Zhaoqi & Zhao, Di & Pu, Xiaorong & Ren, Yazhou. (2021). EEGDnet: Fusing Non-Local and Local Self-Similarity for 1-D EEG Signal Denoising with 2-D Transformer.

Models evaluation

Dataset

- Data
  - EEGDnet dataset
  - No channels
  - 256 Hz
  - epoch length 512 (2 seconds)
  - 4514 EEG epochs
  - 3400 ocular artifact epochs
  - 5598 muscle artifact epochs
  - Mixed signals are generated via $y = x + \lambda n$ with a uniformly distributed SNR from -7dB to 2d (x10 to dataset size)

Zhang, H.; Zhao, M.; Wei, C.; Mantini, D.; Li, Z.; and Liu, Q. 2020. EEGdenoiseNet: A benchmark dataset for deep learning solutions of EEG denoising. *arXiv preprint arXiv:2009.11662*.



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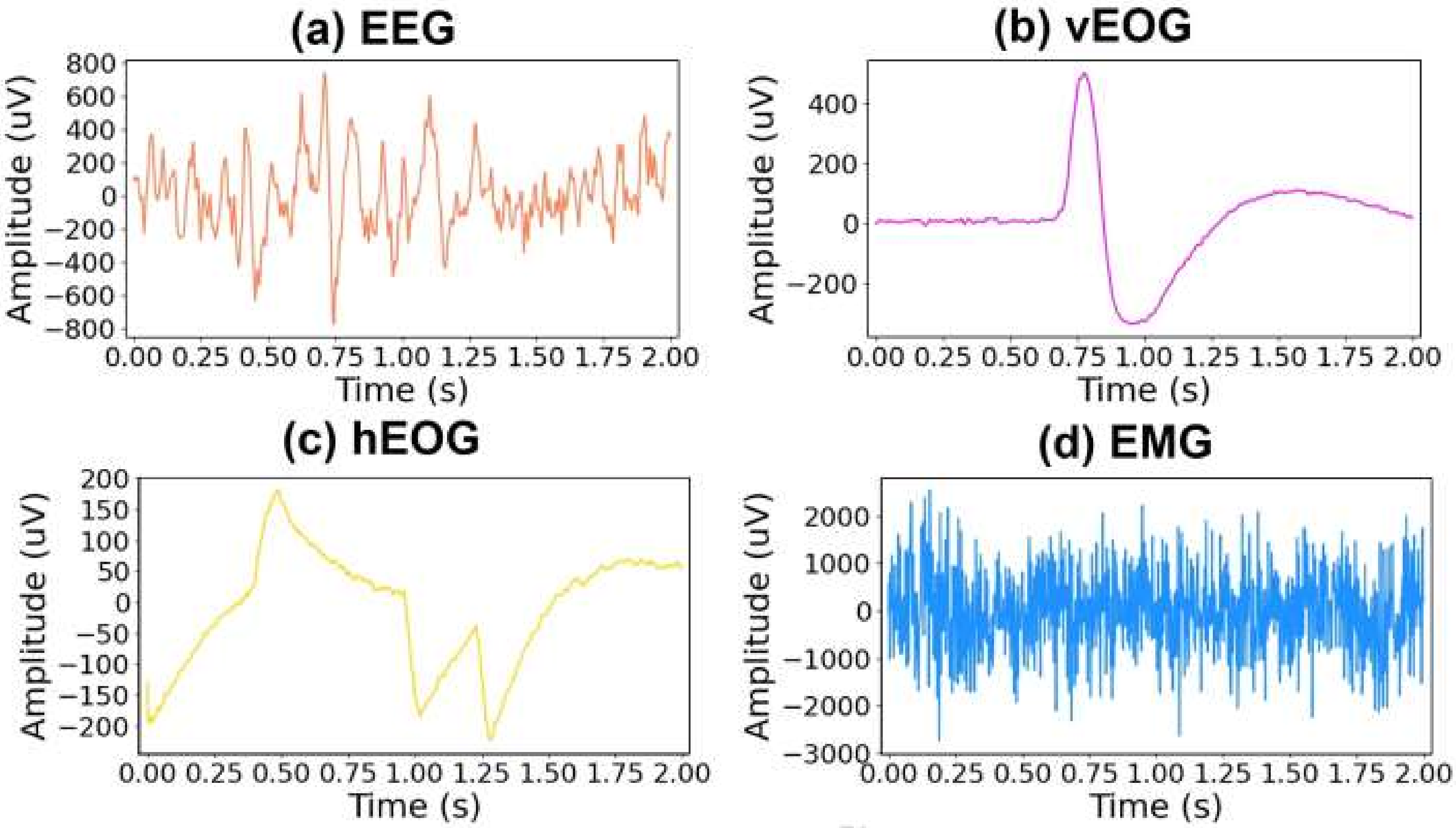
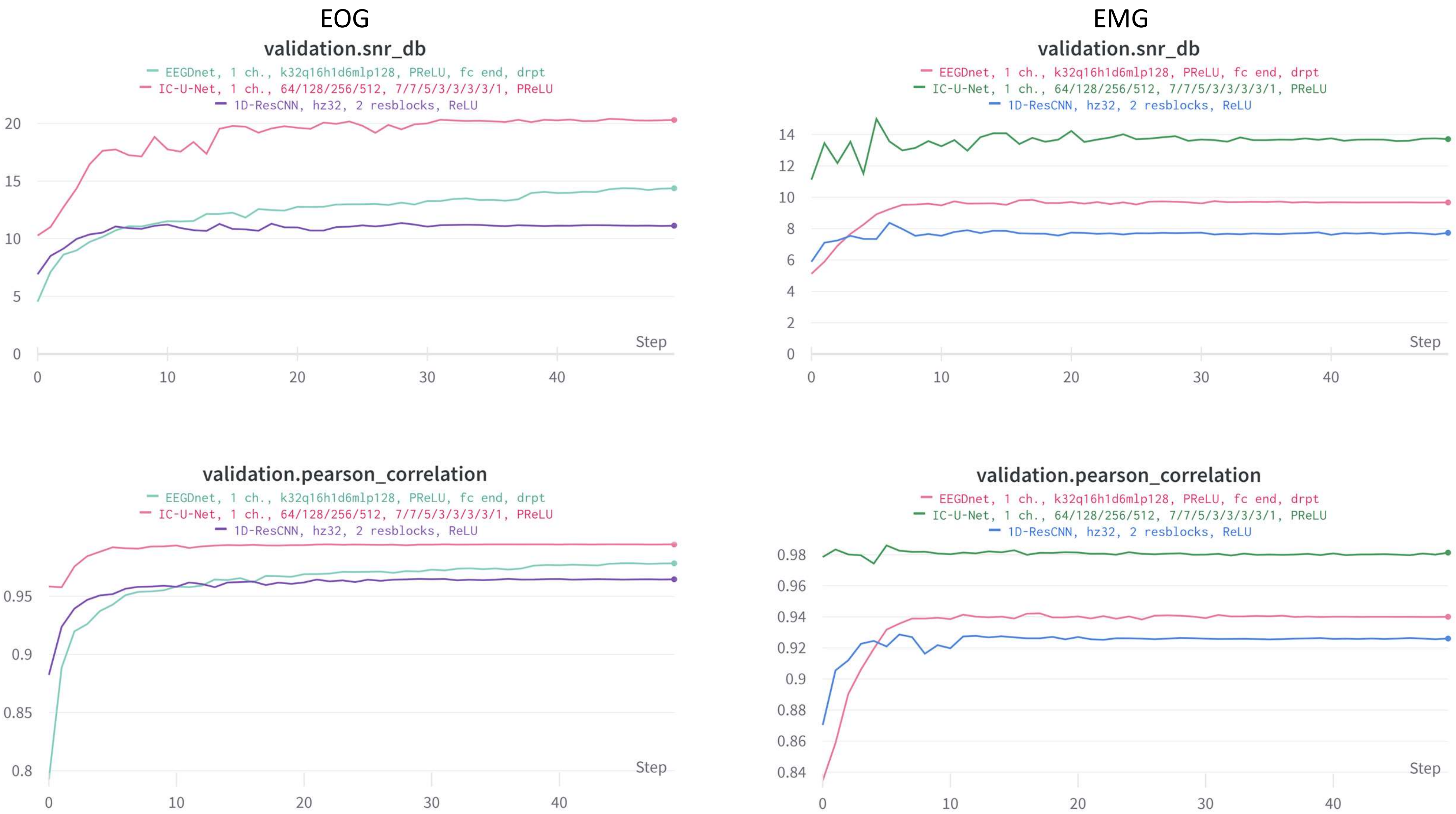


Zhang, H.; Zhao, M.; Wei, C.; Mantini, D.; Li, Z.; and Liu, Q. 2020. EEGdenoiseNet: A benchmark dataset for deep learning solutions of EEG denoising. *arXiv preprint arXiv:2009.11662*.

Dataset

- Dataset
  - 4514 EEG epochs
  - 3400 ocular artifact epochs
  - 5598 muscle artifact epochs
  - Mixed signals are generated via $y = x + \lambda n$ with a uniformly distributed SNR from -7dB to 2d (x10 to dataset size)
  - Resulting size of dataset (80/10/10 split):
    - EOG: train=27200, validation=3400, test=3400
    - EMG: train=36112, validation=4514, test=4514

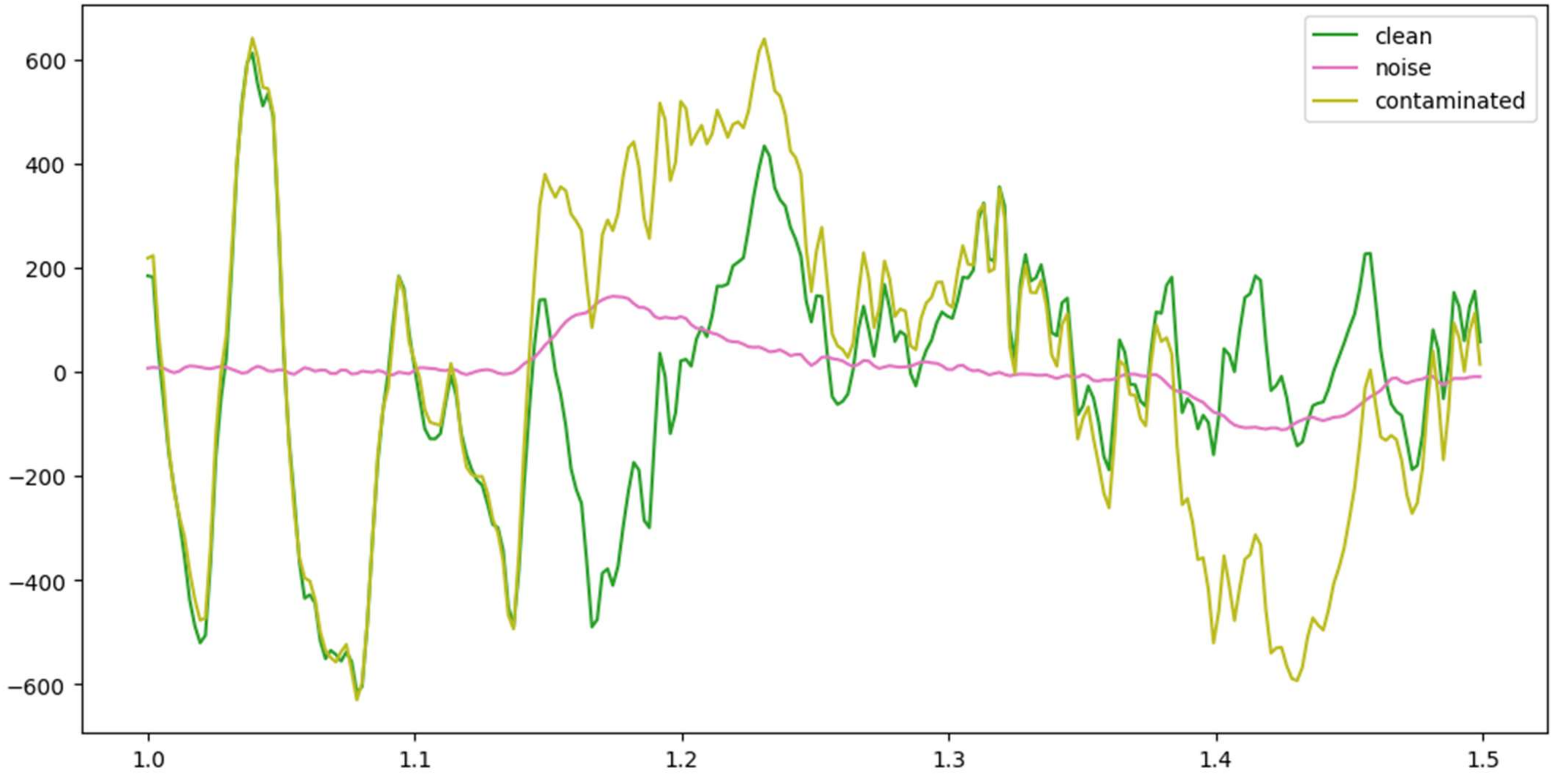
Zhang, H.; Zhao, M.; Wei, C.; Mantini, D.; Li, Z.; and Liu, Q. 2020. EEGdenoiseNet: A benchmark dataset for deep learning solutions of EEG denoising. *arXiv preprint arXiv:2009.11662*.


EOG
validation.snr_db
EEGDnet, 1 ch., k32q16h1d6mlp128, PReLU, fc end, drpt
IC-U-Net, 1 ch., 64/128/256/512, 7/7/5/3/3/3/3/1, PReLU
1D-ResCNN, hz32, 2 resblocks, ReLU
Step
EMG
validation.snr_db
EEGDnet, 1 ch., k32q16h1d6mlp128, PReLU, fc end, drpt
IC-U-Net, 1 ch., 64/128/256/512, 7/7/5/3/3/3/3/1, PReLU
1D-ResCNN, hz32, 2 resblocks, ReLU
Step
validation.pearson_correlation
EEGDnet, 1 ch., k32q16h1d6mlp128, PReLU, fc end, drpt
IC-U-Net, 1 ch., 64/128/256/512, 7/7/5/3/3/3/3/1, PReLU
1D-ResCNN, hz32, 2 resblocks, ReLU
Step
validation.pearson_correlation
EEGDnet, 1 ch., k32q16h1d6mlp128, PReLU, fc end, drpt
IC-U-Net, 1 ch., 64/128/256/512, 7/7/5/3/3/3/3/1, PReLU
1D-ResCNN, hz32, 2 resblocks, ReLU
Step

Results

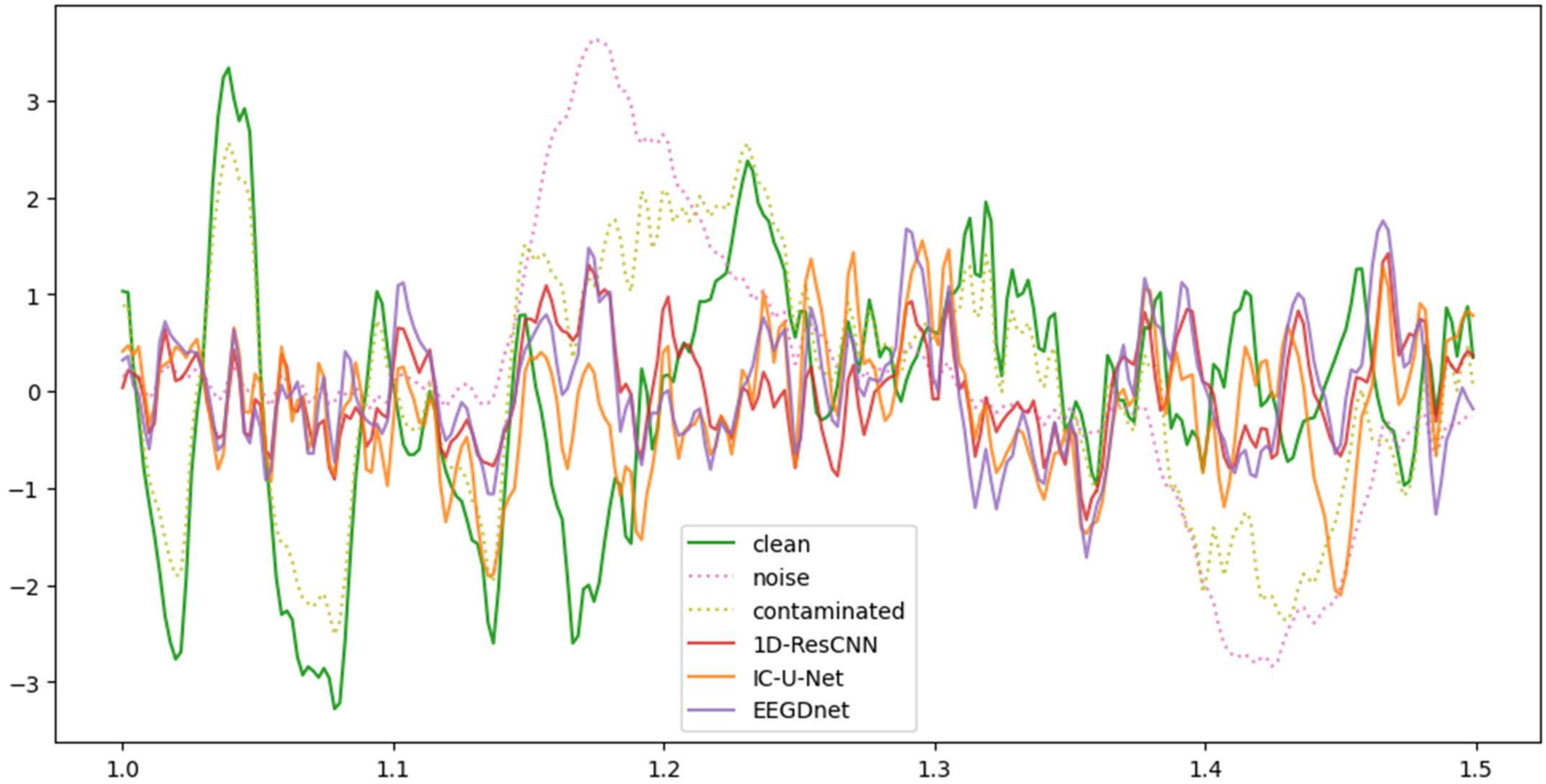
	EOG MSE	EOG SNR, db	EOG CC	EMG MSE	EMG SNR, db	EMG CC
1D-ResCNN	40.643	11.405	0.965	78.022	8.369	0.929
IC-U-Net	**5.791**	**20.523**	**0.995**	**17.296**	**14.947**	**0.986**
EEGDnet transformer	22.236	14.467	0.979	57.739	9.861	0.943

EOG example



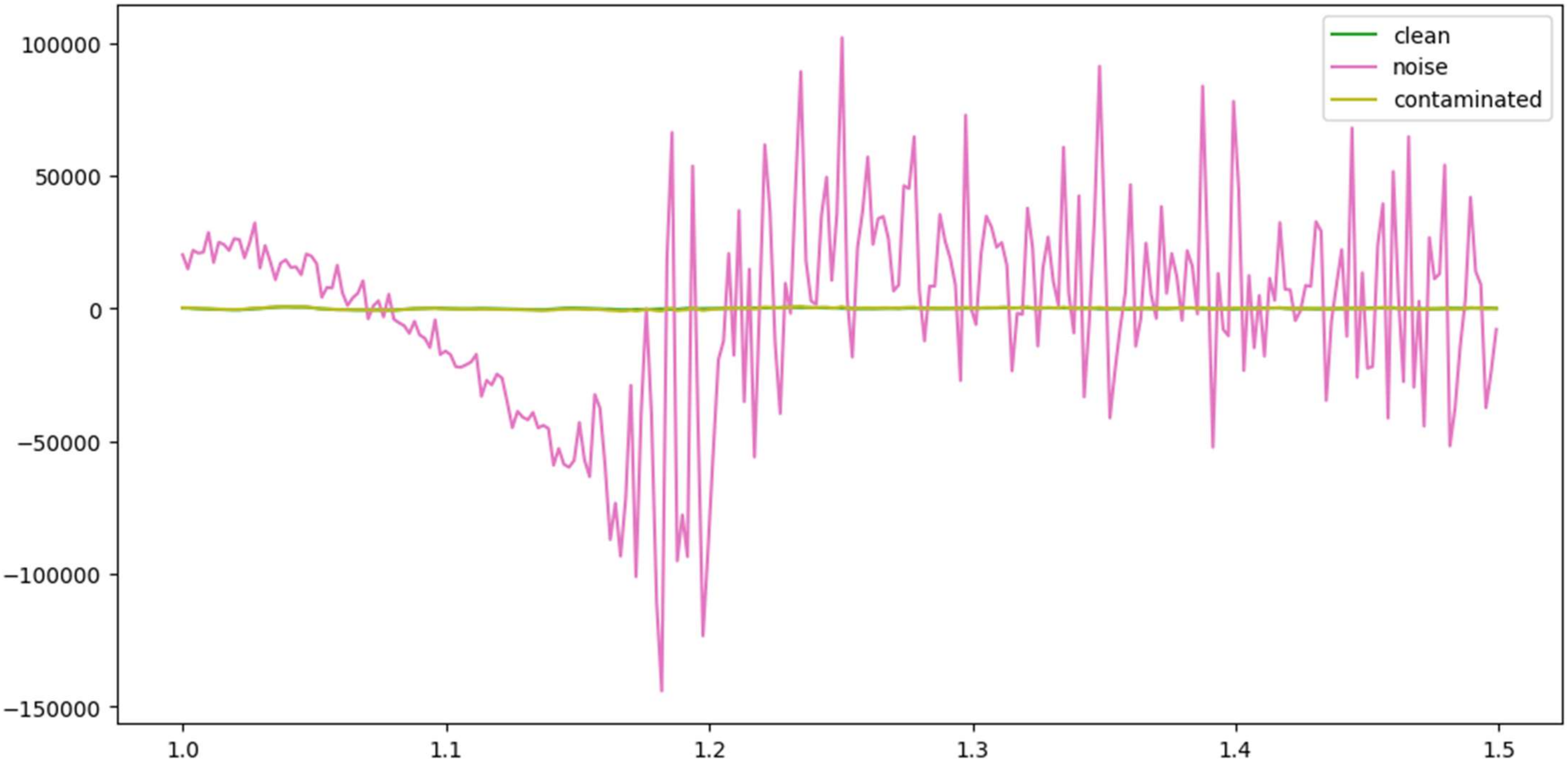
clean
noise
contaminated
600
400
200
0
−200
−400
−600
1.0
1.1
1.2
1.3
1.4
1.5

EOG example



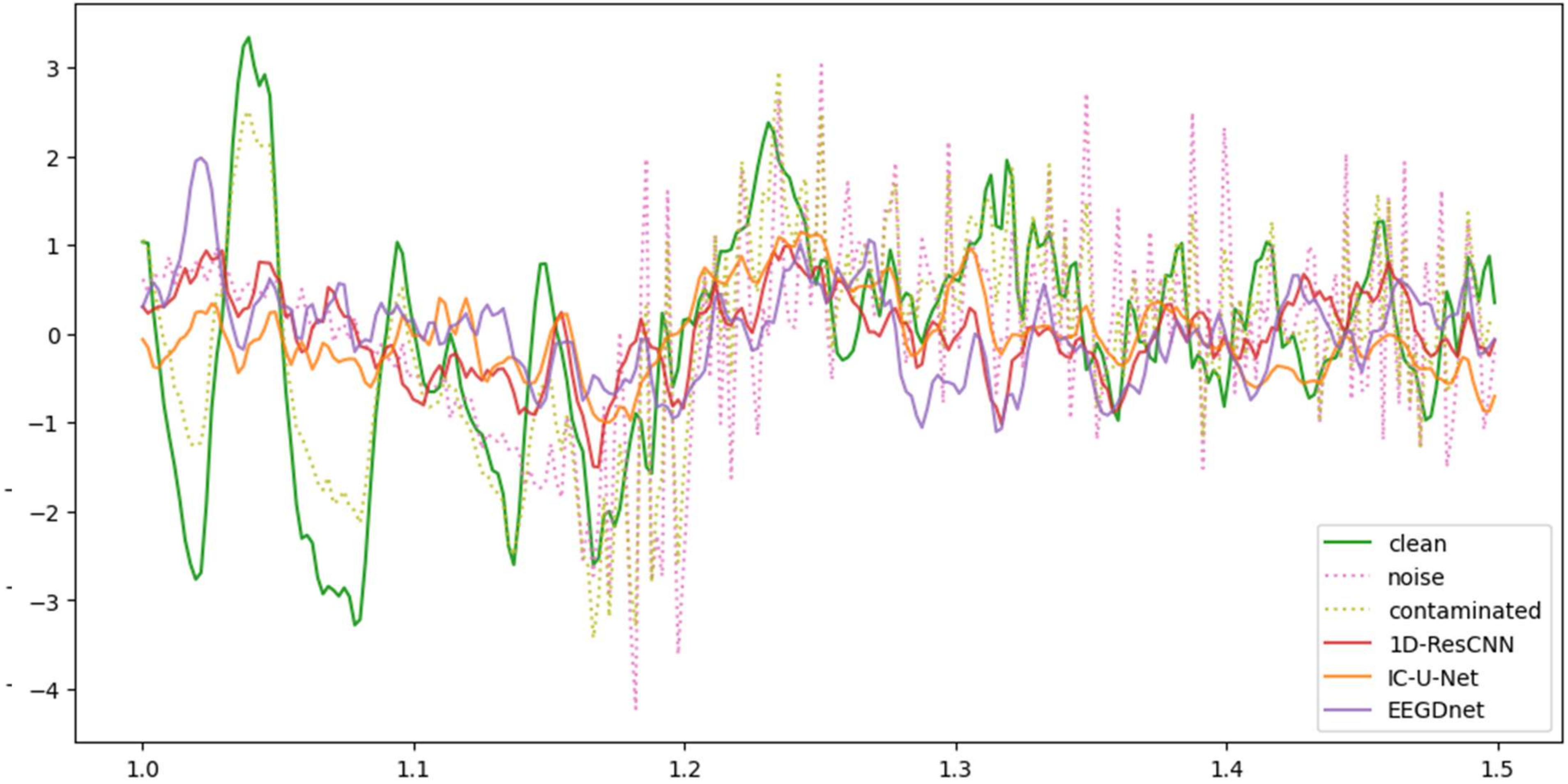
3
2
1
0
−1
−2
−3
1.0
1.1
1.2
1.3
1.4
1.5
clean
noise
contaminated
1D-ResCNN
IC-U-Net
EEGDnet

EMG example



clean
noise
contaminated
100000
50000
0
−50000
−100000
−150000
1.0
1.1
1.2
1.3
1.4
1.5

EMG example



3
2
1
0
−1
−2
−3
−4
1.0
1.1
1.2
1.3
1.4
1.5
clean
noise
contaminated
1D-ResCNN
IC-U-Net
EEGDnet

Amount of parameters

model	trainable	total
1D-ResCNN	325891	325891
IC-U-Net	2777943	2777943
EEGDnet transformer	675398	675398

Conclusion

- IC-U-Net outperformed 1D-ResCNN and EEGDnet transformer architectures in training during 50 epochs;
- There is a lack of public dataset containing information about channels;
- Tone of the considered models use relationships between channels in their architecture, which can be useful.

Training

- batch size: 128
- optimizer: AdamW(lr=1e-3)
- scheduler: ReduceLROnPlateau(factor=0.5, patience=3)
- number of epochs: 50