U-EEG: A Deep Learning Autoencoder for the Detection of Ocular Artifact in EEG Signal

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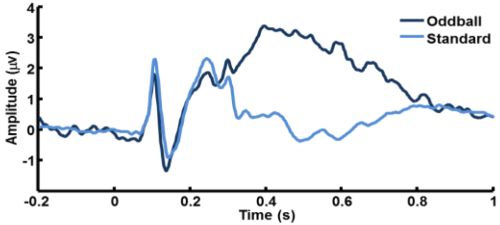
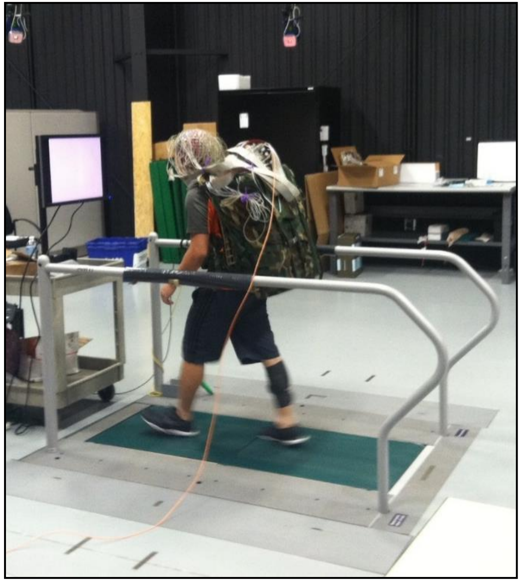
Background

- Intelligent Sensing Branch
  - Biosensor R&D
  - Monitoring cognitive state changes
  - Understanding neural classifier capability in real-world settings

- Working towards fieldable BCI
  - Machine Learning Integration
    - Classification (EEGNet)
    - Filtering (ICA, Neural Nets, etc.)
  - Practicality

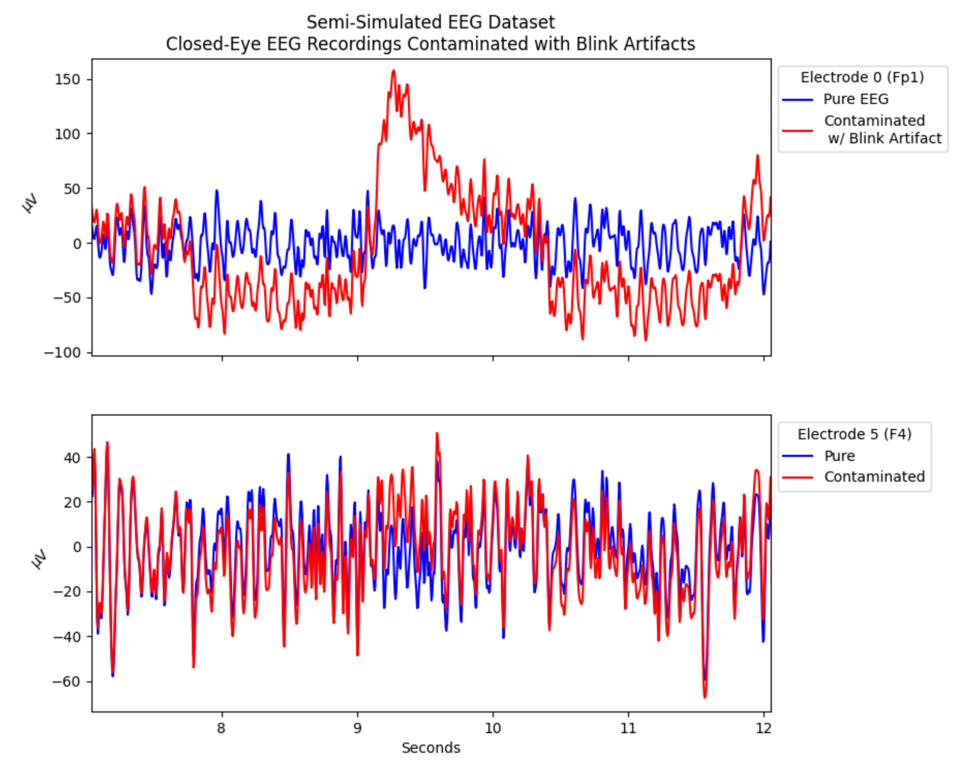




Problem Description

- Project Goal: Improved BCI Classification Capability

- Issue: Noise
  - What do we consider noise in EEG?
    - System/Electrical Noise
    - Blinking (EOG)
    - Walking/Muscle Activity (EMG)
  - How do different types of noise affect classification accuracy?



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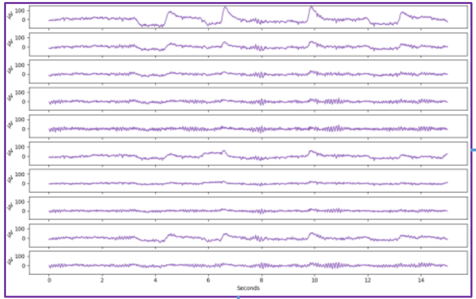
Problem Description

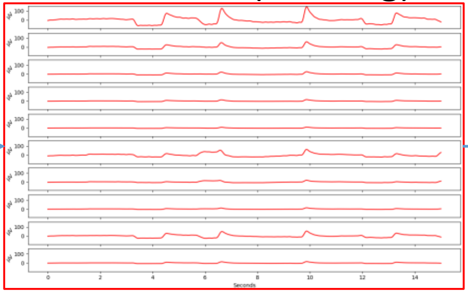
Contaminated



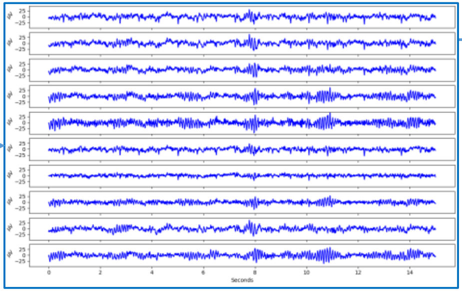
Classifier (EEGNet)

Classification Label (Accuracy: X%)

Artifact 1 (Blinking)



Pure 1



EEGNet

Classification Label (Accuracy: X±A1%)

Artifact 2 (Walking)

Pure 2

EEGNet

Classification Label (Accuracy: X±A2%)

Artifact 3 (Other Noise)

Pure 3

EEGNet

Classification Label (Accuracy: X±A3%)

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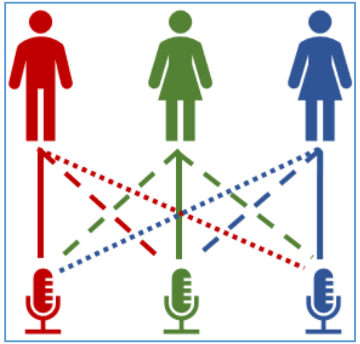
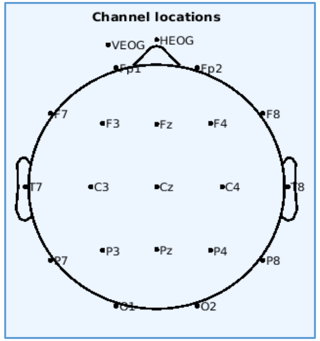
Current Solution: ICA

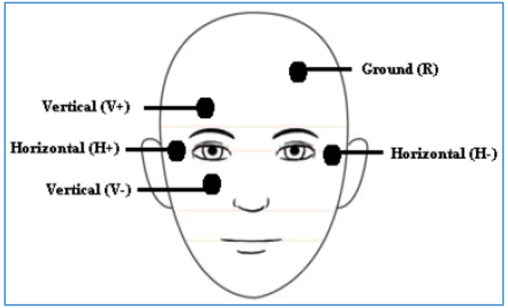
- Independent Component Analysis
  - Blind Source Separation (Cocktail Party Problem)
  - Maximize Independence between multiple recording sources



https://infinitymesh.com/media/1171/cocktailpartyrecordingspeech.png?width=287&height=278

- Standard ICA Issues
  - Electrode/Time dependent
  - Generally requires manual intervention
  - Noise References
    - Inconvenient for practical BCI usage
  - Timing Constraints





https://www.biomedres.info/articles-images/biomedres-Electrode-placement-29-6-1078-g001.png

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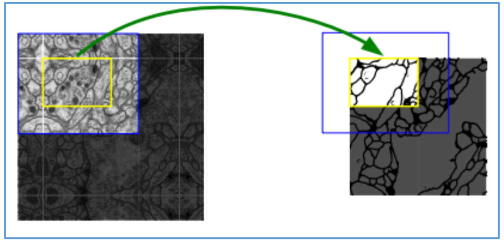
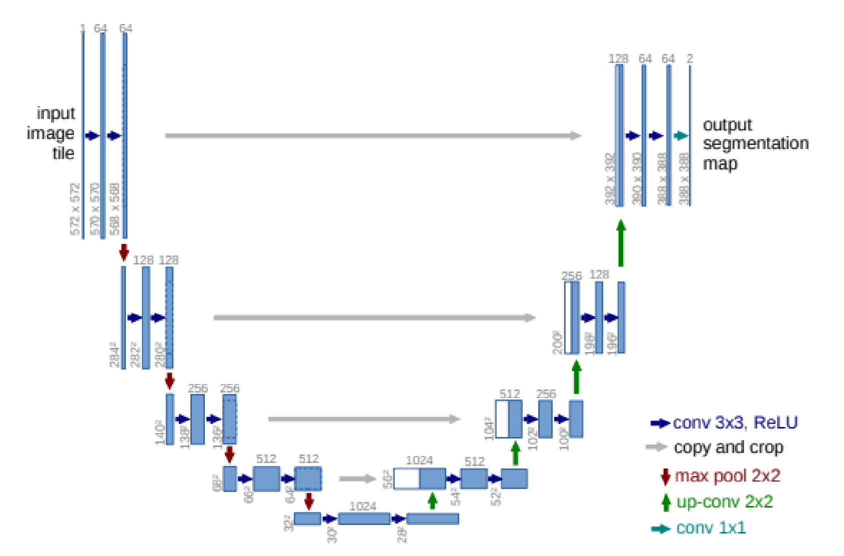
Potential Solution: U-Net

- CNN encoder/decoder pipeline that reincorporates early layer outputs to later layer inputs
- Provides higher-resolution context to compressed channels/feature-maps
- Able to easily create a full output mask with the same shape as the input





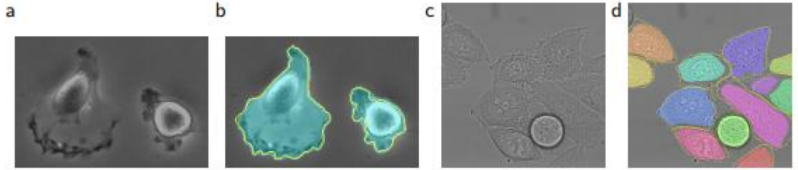


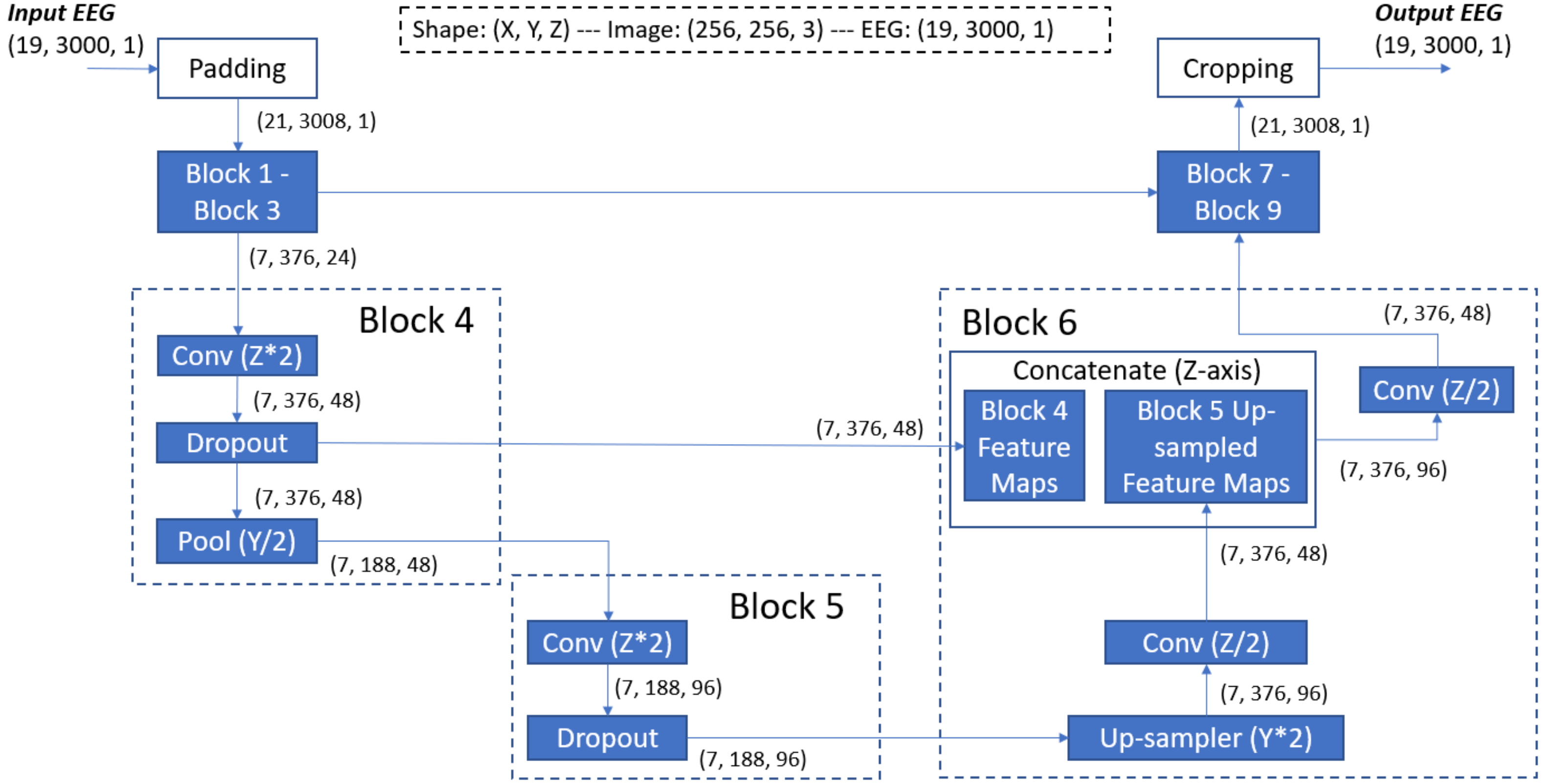
Fig. 4. Result on the ISBI cell tracking challenge. (**a**) part of an input image of the "PhC-U373" data set. (**b**) Segmentation result (cyan mask) with manual ground truth (yellow border) (**c**) input image of the "DIC-HeLa" data set. (**d**) Segmentation result (random colored masks) with manual ground truth (yellow border).

Table 2. Segmentation results (IOU) on the ISBI cell tracking challenge 2015.

Name	PhC-U373	DIC-HeLa
IMCB-SG (2014)	0.2669	0.2935
KTH-SE (2014)	0.7953	0.4607
HOUS-US (2014)	0.5323	-
second-best 2015	0.83	0.46
u-net (2015)	**0.9203**	**0.7756**

https://arxiv.org/abs/1505.04597

U-Net Layer Output Shape Example



Semi-Simulated Dataset

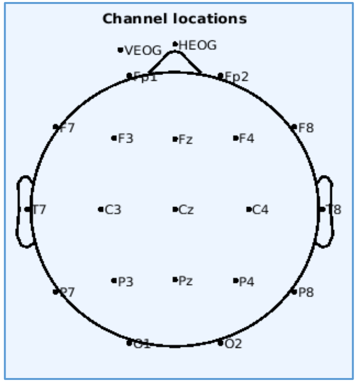
- Public Dataset: M. A. Klados and P. D. Bamidis, "*A semi-simulated EEG/EOG dataset for the comparison of EOG artifact rejection techniques*"
- 19 Channel EEG
  - 10-20 International System Electrode Placement
- 2 Channel EOG
  - VEOG: 2 electrodes above and below left eye (vertical – VEOG),
  - HEOG: 2 electrodes on the outer canthi of both eyes (horizonal – HEOG)
- 30s Closed-Eye Sessions:
  - Pure EEG (minimal EOG interference, Ground Truth)
- 30s Open-Eye Sessions:
  - VEOG and HEOG noise references
  - Raw EEG (high EOG interference, used to calculate subject's EOG contribution at each electrode)

- Experimental signal (*Contaminated*) calculated using:

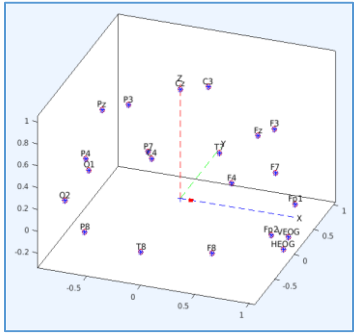
$$Contaminated_{i,j} = Pure_{i,j} + a_j(VEOG_i) + b_j(HEOG_i) \quad (1)$$

Where: ***a*** = VEOG Scalar, ***b*** = HEOG Scalar, ***i*** = Subject Number, ***j*** = Electrode

- Allows for a 'True' Ground Truth to easily compare filtering methods
- Dataset Dimensions: 54 Batches, 19 Channels and 6000 Samples Per Batch

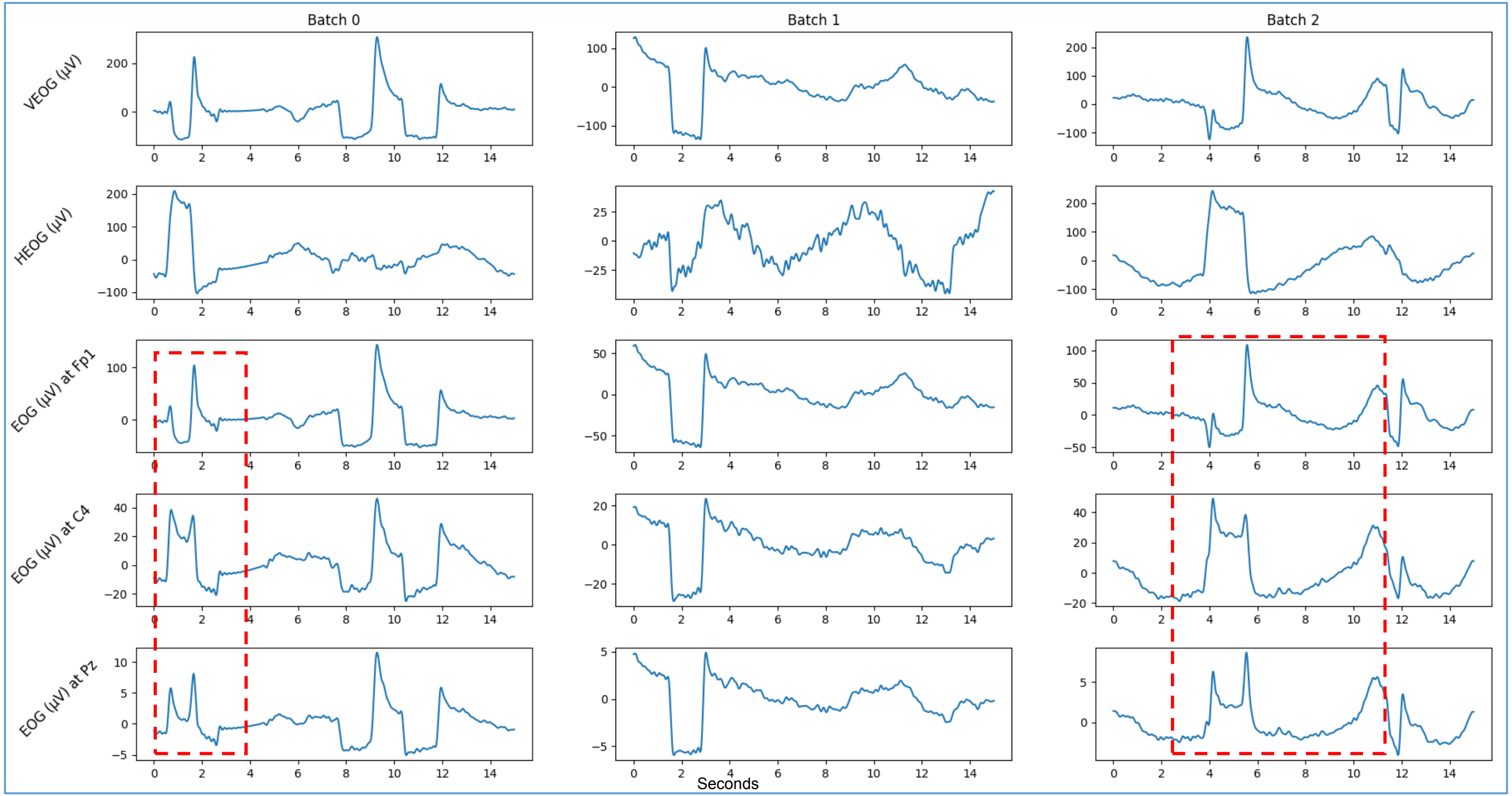


EEGLab Channel Locations (2D View)



EEGLab Channel Locations (3D View)

Semi-Simulated Dataset

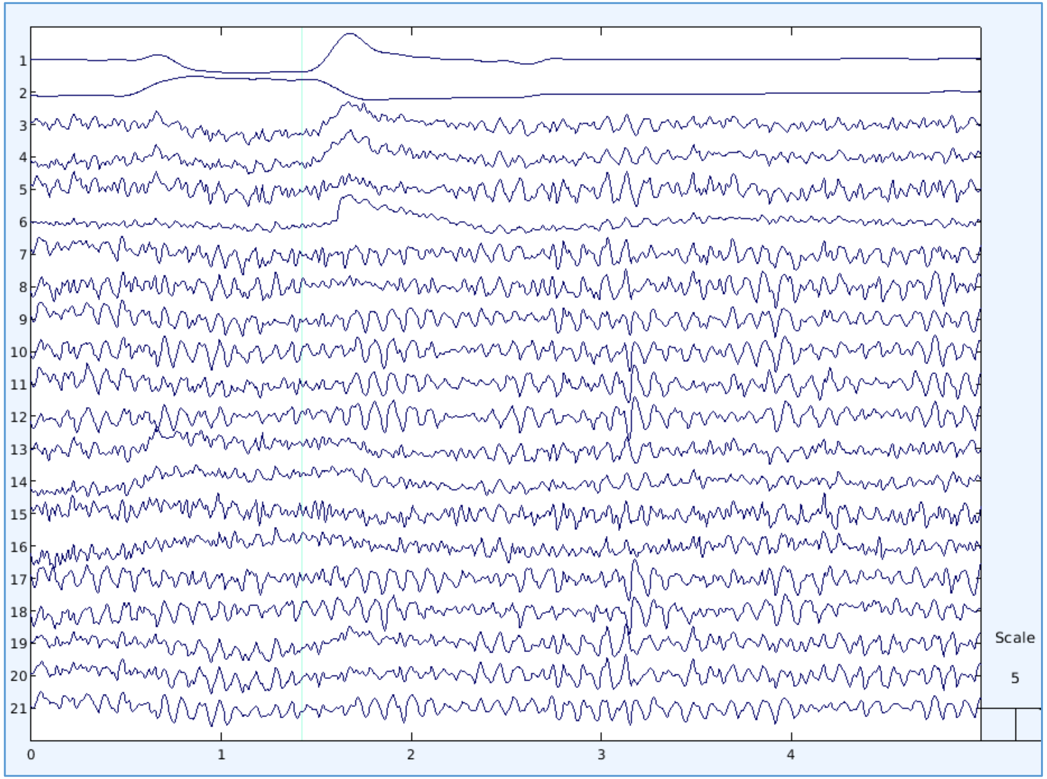


*Note: Y-axis scaling applied for visualization purposes

EEGLAB ICA (Control)

- Loaded 19-channel *Contaminated* and additional VEOG and HEOG channels
- "Decomposition by ICA"
  - Maximizes component independence at each electrode
- Reject VEOG and HEOG channels and its contribution at all other electrodes (ICA_{Pure})
- Estimated artifact can be computed as:

$$ICA_{EOG} = Contaminated - ICA_{Pure} \quad (4)$$



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U-EEG (Experimental)

- Modified Public U-Net
  - https://github.com/zhixuhao/unet
  - Limited Hyperparameter modifications
  - Layer shape modifications
- Keras CNN layers
  - 2D Functions
  - i.e. MaxPooling = keras.layers.MaxPooling2D()
  - Padding: ‘same’
  - Activations: ELU
- Input: Raw EEG
  - In this case, semi-simulated EEG
- Output: Predicted EOG mask
  - Larger variance compared to Predicted Pure signal
- Compute Predicted Pure Using:

$$U\text{–}EEG_{pure} = Contaminated - U\text{–}EEG_{EOG} \quad (3)$$

Table 1. U-EEG input and output dimension.

Block No.	Input Dimensions	Layers	Output Dimensions
0	E, S, None	ExpandDims ZeroPadding	(E+Pe), (S+Ps), 1
1	(E+Pe), (S+Ps), 1	Conv MaxPooling	(E+Pe), (S+Ps)/2, C
2	(E+Pe), (S+Ps)/2, C	Conv MaxPooling	(E+Pe), (S+Ps)/4, C*2
3	(E+Pe), (S+Ps)/4, C*2	SeparableConv Dropout AveragePooling	(E+Pe)/3, (S+Ps)/8, C*4
4	(E+Pe)/3, (S+Ps)/8, C*4	Conv Dropout AveragePooling	(E+Pe)/3, (S+Ps)/16, C*8
5	(E+Pe)/3, (S+Ps)/16, C*8	Conv SpatialDropout	(E+Pe)/3, (S+Ps)/16, C*16
6	(E+Pe)/3, (S+Ps)/16, C*16	Unsample Concatenate Conv	(E+Pe)/3, (S+Ps)/8, C*8
7	(E+Pe)/3, (S+Ps)/8, C*8	Upsample Concatenate SeparableConv	(E+Pe), (S+Ps)/4, C*4
8	(E+Pe), (S+Ps)/4, C*4	Upsample Concatenate Conv	(E+Pe), (S+Ps)/2, C*2
9	(E+Pe), (S+Ps)/2, C*2	Upsample Concatenate Conv	(E+Pe), (S+Ps), C
10	(E+Pe), (S+Ps)/2, C	Conv Cropping	E, S, None

Table 2. U-EEG hyperparameters and variable values

Parameter	Value
E (Number of Input Electrodes)	19
Pe (Electrode Dim. Padding)	2
S (Number of Input Samples)	3000
Ps (Sample Dim. Padding)	8
C (Channel Multiplier)	6
Number of Training Batches	71
Number of Validation Batches	8
Number of Testing Batches	8
Optimizer	Adam
Loss Function	Mean Squared Error
Dropout Rate	0.7
Layer Padding Type	Same
Trainable Params	487,229

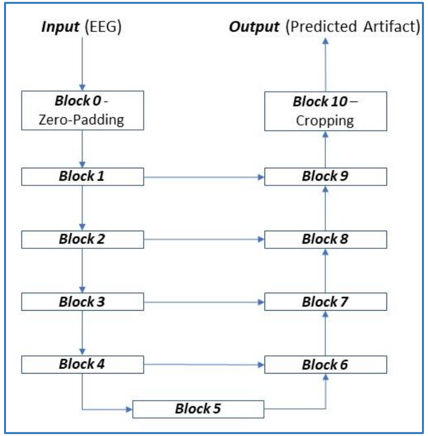

Figure 1. Diagram of U-EEG architecture.

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Results

Table 3. Artifact removal precision (RMSE, µV) on testing data

Electrode	ICA_{Pure}	$U\text{-}EEG_{Pure}$
Fp1	13.817	7.103
Fp2	13.845	6.990
F7	3.823	3.277
F3	3.895	3.167
Fz	1.860	1.561
F4	1.971	1.563
F8	1.256	1.148
T7	1.593	1.071
C3	0.977	0.749
Cz	1.072	0.906
C4	8.274	4.319
T8	8.413	4.233
P7	3.255	1.683
P3	3.299	1.663
Pz	1.178	1.063
P4	1.396	1.004
P8	6.118	3.207
O1	2.831	1.481
O2	1.478	1.028
Mean	***5.793*** ± 1.769	***3.134*** ± 0.893

RMSE per Electrode: $\sqrt{\left(\frac{1}{I}\sum_{i=1}^{I=8}\left(\frac{1}{N}\sum_{n=1}^{N=3000}(Pure_{j,s}-Filtered_{j,s})^2\right)\right)}$

Total: $\sqrt{\left(\frac{1}{I}\sum_{i=1}^{I=8}\left(\frac{1}{J}\sum_{j=1}^{J=19}\left(\frac{1}{N}\sum_{n=1}^{N=3000}(Pure_{j,s}-Filtered_{j,s})^2\right)\right)\right)}$

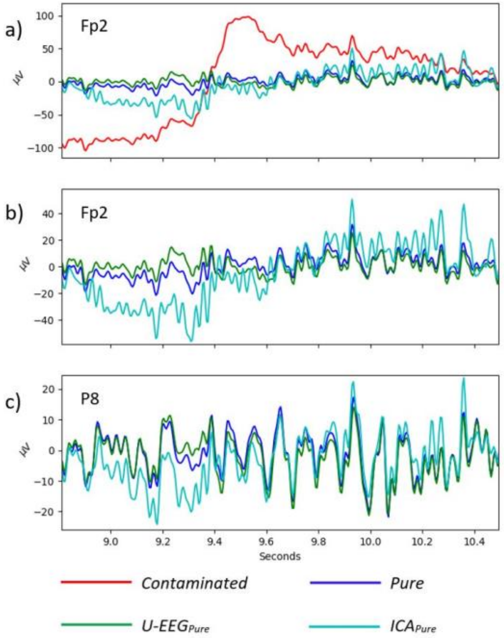

Figure 2. Comparison of U-EEG and ICA filtered EEG signal on test subject 0, depicting randomly selected electrodes Fp2 and P8 within a randomly selected time window (9-10.5 s). Subplot (a) shows *Contaminated*, *Pure*, and the filtered outputs. Traces from Fp2 (b) and P8 (c) show the noise-free signal (*Pure*) and estimates $U\text{-}EEG_{Pure}$ and ICA_{Pure}. For display purposes, the y-axis scale showing EEG amplitude (µV) is not constant across subplots.

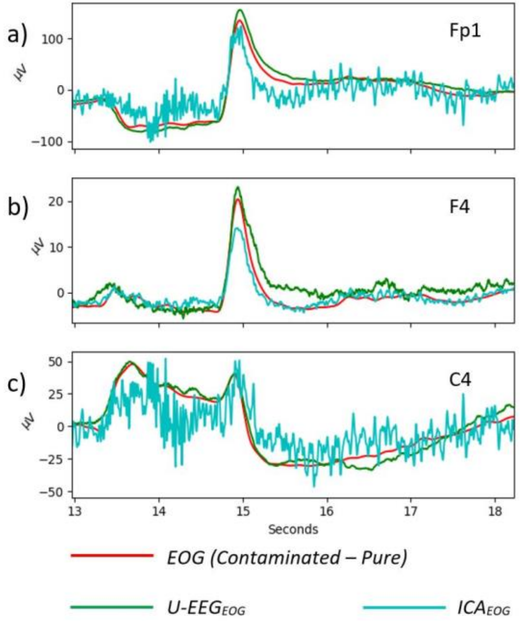

Figure 3. Comparison of U-EEG and ICA EEG artifact detection on test subject 4, depicting randomly selected electrodes Fp1, F4, and C4 within a randomly selected time window (13-18 s). Traces from Fp1, F4, and C4 (a-c) show the EOG artifact (*Contaminated – Pure*) and the EOG estimates $U\text{-}EEG_{EOG}$ and ICA_{EOG}. For display purposes, the y-axis scale showing EEG amplitude (µV) is not constant across subplots.

Conclusions & Future Work

- Our experiment has shown that the U-Net model has potential in the space EEG space
- Current/Future Research Endeavors:
  - Test with Larger Dataset
    - Does the U-Net model only make the most out of limited data batches?
    - Will a larger dataset continue improved accuracy, or does accuracy converge quickly?
  - Test with Different Dataset Shape
    - Increased electrodes, decreased temporal samples, decreased sampling rate, etc.
  - Test on Different Artifacts
    - Loaded/Walking (ICA Cleaned)
  - Add in series with Classifier
  - (Near) Real-Time Application