A deep learning approach to remove motion artifacts in fNIRS data analysis

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Abstract: We established a neural network model to efficiently remove motion artifacts during fNIRS data processing.

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1. Introduction

Motion artifact is a ubiquitous challenge in functional near-infrared spectroscopy (fNIRS) data analysis especially when the experimental design relies upon subject motion. Hence, different signal processing methodologies have been proposed over the years to filter out these motion artifacts to recover with accuracy cortical activations from fNIRS time-series data. Still, recently, deep learning (DL) techniques have been shown as a suitable techniques to remove noise in biological data in a fast and efficient manner [1]. Herein, we report on the first foray in using a DL model to tackle this difficult task in fNIRS. First, we designed different convolution neural network (CNN) architecture to identify the best one. To assess the performances of each architecture, we simulated a fNIRS data set employed both for training and validation. Then, upon successful validation of the training paradigm and identification of the best architecture, termed 'CNNIRS', we benchmarked CNNIRS performances against established denoising technique used in the field, including spline, wavelet and Kalman filters. Overall, we report that CNNIRS outperforms all these established filtering techniques both in terms of computational efficiently but also accuracy as reported by the mean squared error (MSE) metric. Hence, CNNIRS is well positioned to facilitate fNIRS data set analysis.

2. Methods

2.2 Neural network model setup and training

Inspired by the model structure in [1], we set up four CNN based 'encoders-decoders' models: '4-layer', '4-layer+dropout', '8-layer' and '8-layer+dropout'. The '4-layer' model and '8-layer' model structures are shown in Table 1 and Table 2. Based on these two models, the '4-layer+dropout' model and '8-layer+dropout' model were created by adding dropout (0.1) layers after the Maxpooling (MP) and Upsampling (US) layers. We set mean square error (MSE) as the loss function and used 'Adam' optimizer. The models were adequately trained by 1000 epochs with the best one saved. The learning rate was set to 0.000001 and decayed by 2 per 100 epochs.

Table 1. '4-layer' model

Layer	Input	Conv1	MP1	Conv2	MP2	Conv3	US1	Conv4	US4	Conv5
Output size	512×1	512×32	256×32	256×32	128×32	128×32	256×32	256×32	512×32	512×1

Table 2. '8-layer' model

Layer	Input	Conv1	MP1	Conv2	MP2	Conv3	MP1	Conv4	MP4	Conv5
Output size	512×1	512×32	256×32	256×32	128×32	128×32	64×32	64×32	32×32	32×1
Layer	UP1	Conv6	UP2	Conv7	UP3	Conv8	UP4	Conv9		
Output size	64×32	64×32	128×32	128×32	256×32	256×32	512×32	512×1		

2.2. fNIRS data simulation

To simulate fNIRS data set with features that are closely matching experimental settings we followed the approach as laid out in [3]. First, we fitted autoregressive (AR) models into the fNIRS data which were collected from our previous study [2]. Based on the averaged AR parameters derived, we simulated the resting state fNIRS signal through Matlab's Econometrics toolbox [3]. The evoked responses were simulated by gamma function [3]. The spike motion artifacts were simulated by Laplace distribution function [3]. Shift artifacts were modeled as a random value change [3]. All fNIRS data simulated were time series with a total length of 20sec each at a sampling rate of 25Hz. To validate the performances and the robustness of various CNNs architecture, three fNIRS data sets were generated differing by their overall size, i.e., 500, 1000 and 5000. The portion of training, validation, testing data were split by the ratio 8:1:1.

3. Results

3.1 Model training results

The testing MSEs for each model and data set size are presented in Table 3. The '8-layer' model trained overall exhibit the lowest MSEs for all data set size considered herein. Hence, the '8-layer' model trained with 5000 samples was retained for the rest of the study ('CNNIRS').

Table 3. Mean squared error for neural networks

Data sample size	500	1000	5000
'4-layer' model	6.65	6.53	7.61
'4-layer+dropout' model	11.47	11.00	8.40
'8-layer' model	3.43	3.49	**3.03**
'8-layer+dropout' model	8.47	9.28	10.73

3.2 Comparison between models

The CNNIRS model was benchmarked against 'No correction', spline, wavelet and Kalman filters. When applied to a new simulated sample of 330 pieces of fNIRS data (ten 20s samples of 33-channel data with the same probe geometry with [2]). The CNNIRS model demonstrated the lowest MSE overall (Fig. 1).

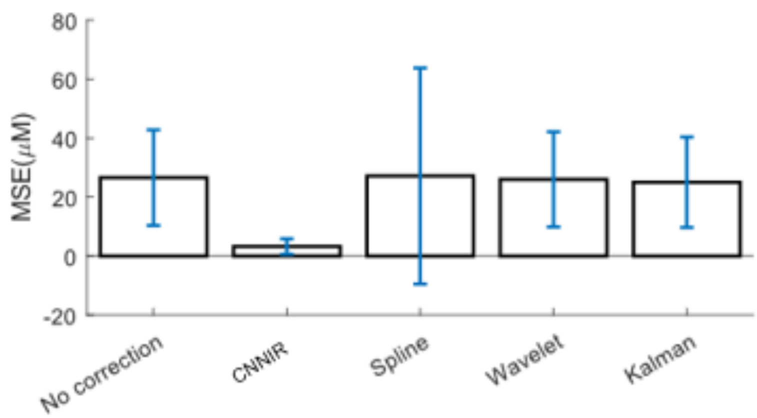

Fig. 1. Mean and standard deviation of mean square error for the different motion artefacts removal methodologies tested.

4. Conclusion

We introduced a deep learning model to remove the motion artifacts in fNIRS model. This *in silico* study demonstrated that our CNNIRS model has higher accuracy than commonly used methods. We are currently applying this new approach on experimental data and will further explore its application in real world problem solving.

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6. References

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