

On the Reliability of Frequency-Domain Features for fNIRS BCIs in the Presence of Pain

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This work was supported by NSF

12/04/2021

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- Background
- Motivation

• Methods

- Experimental Design
- Analysis
- Results
- Conclusions





• functional Near Infrared Spectroscopy (fNIRS)

- Brain activation causes changes in the concentration of
 - Oxy hemoglobin [HbO]
 - Deoxy hemoglobin [HbR]







1. N. Naseer, et al. "fNIRS-based brain-computer interfaces: a review", *Frontiers in human* neuroscience, vol. 9, pp. 3, 2015.

2. M. Abtahi, et al. "Hand Motion Detection in fNIRS Neuroimaging Data." *Healthcare*. vol. 5, no. 2, 2017.





- Brain Computer Interfaces (BCIs):
 - An interface between brain and an external device to control the device using the brain
 - Key applications : Assistive interfaces for disabled patients



• fNIRS-Based BCIs:

- Use fNIRS for brain signal acquisition
- Advantages :
 - Non-invasive, low cost, easy to use, portable
 - No vulnerability to electromagnetic environment
 - Relatively low sensitivity to head motion artifacts as compared to EEG and fMRI





• Most BCI Users Are Patients Who Experience Pain

- Often, pain is prevalent in patients with motor disabilities could be chronic or acute in nature
- Pain is expected to impact cortical activity related to the task at hand [3]
- This in turn would impact the BCI performance potentially resulting in failure of assistive devices







- Goals of This Study
 - Study the impact of the presence of pain on the classification accuracy of fNIRS-based BCIs
 - Explore the impact of cortical region-based channel selection on the classification accuracy of BCIs





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• Four Cases Are Considered To Study The Impact of Pain







• fNIRS Recordings

- Experimental setup for data collection : NIRx system (sampling rate: 10.41 Hz)
- Channels:
 - number: 50 (16 sources and 24 detectors)
 - location: prefrontal and motor cortices
 - source-detector separation: 3 cm







Pain Stimulation

- TSA-II Medoc System
- 30 × 30 mm standard thermode
- Painful stimuli on dorsum of left hand



TSA-II system.





Standard thermode

The thermode attached to the subject's dorsum of the left hand

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Experimental Design



Pain Threshold And Tolerance Measurement





RUTGERS

Experimental Paradigm

- 3 healthy right-handed subjects
- 5 no-pain and 5 pain blocks in random order
- 2 classes of mental arithmetic tasks
 - o mental subtraction
 - o mental back counting
- $T_{\rm stim}$ (stimulus temperature) for pain blocks and baseline temperature (32°C) for no-pain blocks
- 65 trials of each task were recorded under pain and no-pain conditions



Visual illustration of a single trial.





• Preprocessing

- [ΔHbO] signal from [0-6] sec window
- Drifts and artifact removal using nirsLAB [1]
- Bandpass filtering [0.01-0.2] Hz
- Baseline correction (baseline: [-1~0])

Feature Extraction

- Features from frequency domain representation of [ΔHbO] signal from all channels using discrete Fourier transform (DFT) and power spectral density
 - o maximum value of power spectral density
 - median value of power spectral density
 - \circ variance of power spectral density
 - \circ maximum value of real part of DFT
 - \circ $\,$ frequency corresponding to maximum value of real part of DFT $\,$
 - \circ $\ \$ frequency corresponding to maximum value of power





• Classification

- Support vector machine with quadratic kernel (QSVM)
- Training and validation: 75%, testing: 25%
- 10-fold cross-validation to avoid overfitting





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- Classification Results For 4 Cases Of Training And Testing, Using Data From All 50 Channels Covering PF And Motor Cortices
 - Presence of pain impacts classification accuracy and lowers the accuracy to the chance levels
 - It is essential to consider the presence of pain in developing BCI algorithms for patients

	Case 1 Train (no-pain) Test (no-pain)	Case 2 Train (no-pain) Test (pain)	Case 3 Train (pain) Test (pain)	Case 4 Train (pain) Test (no-pain)
Maximum of PSD	84.87± 2.2	50.72± 2.5	85.09± 2.3	50.63± 2.6
Median of PSD	85.09± 2	51.09± 2.3	85.02± 2.2	50.54± 2.5
Variance of PSD	76.60± 2.6	50.46± 2.4	76.02± 2.3	50.72± 2.7
Maximum value of real part of DFT	88.65± 1.9	52.68± 2.6	89.91±1.7	53±2.3
Frequency of Maximum value of real part of DFT	81.47± 1.9	50.51± 2.7	83.14± 2.7	50.52± 2.3
Frequency of maximum power	50.43± 2.4	50.71± 2.2	49.96± 2.1	50.85± 2.4





- Classification Results For The 4 Cases, Using PF Cortex Channels Only
 - For case 1 and case 3, use of only the PF channels lowers the classification accuracy
 - For case 2 and case 4, results still remain at chance level

	Case 1 Train (no-pain) Test (no-pain)	Case 2 Train (no-pain) Test (pain)	Case 3 Train (pain) Test (pain)	Case 4 Train (pain) Test (no-pain)
Maximum of PSD	71.08± 2.2	54.13± 2.4	72.49±2.2	53.75±2.2
Median of PSD	71.56± 1.9	54.72± 2.3	72.68±2.4	54.05±2.4
Variance of PSD	56.81± 4.8	51.63± 2.7	60.29±3.2	50.78±2.6
Maximum value of real part of DFT	72.24± 2.2	52.4± 2.6	73.65±2	53.52±2.5
Frequency of Maximum value of real part of DFT	63.01± 2.3	51.83± 3	65.54±2.3	50.69±2.2
Frequency of maximum power	49.36± 2.1	49.67± 2.1	48.80±2	49.22±2.4





- Classification Results For The 4 Cases, Using Motor Cortex Channels Only
 - For case 1 and case 3, use of only the motor channels again lowers the classification accuracy
 - For case 2 and case 4, results still remain at chance level

Case 1 Train (no-pain) Test (no-pain)	Case 2 Train (no-pain) Test (pain)	Case 3 Train (pain) Test (pain)	Case 4 Train (pain) Test (no-pain)
83.26±2.1	50.36±2.3	82.75±2.3	50.92±2.4
83.91±2.1	50.22±2.3	83.07±2.3	50.57±2.3
75.60±2.3	50.27±2.6	73.69±2.6	50.95±2.6
86.60±2	52.32±2.6	87.09±1.9	51.60±2.7
77.41±1.9	50.63±2.4	80.13±1.9	50.13±2.5
49.74±2.2	51±2.1	50.82±2.4	50.47±2.4
	Case 1 Train (no-pain) Test (no-pain) 83.26±2.1 83.91±2.1 75.60±2.3 86.60±2 77.41±1.9 49.74±2.2	Case 1 Train (no-pain) Test (no-pain) Case 2 Train (no-pain) Test (pain) 83.26±2.1 50.36±2.3 83.91±2.1 50.22±2.3 75.60±2.3 50.27±2.6 86.60±2 52.32±2.6 77.41±1.9 50.63±2.4 49.74±2.2 51±2.1	Case 1 Train (no-pain) Test (no-pain)Case 2 Train (no-pain) Test (pain)Case 3 Train (pain) Test (pain)83.26±2.150.36±2.382.75±2.383.91±2.150.22±2.383.07±2.375.60±2.350.27±2.673.69±2.686.60±252.32±2.687.09±1.977.41±1.950.63±2.480.13±1.949.74±2.251±2.150.82±2.4





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- The presence of pain significantly impacts the cortical activity. Thus, a model trained on pain-free data but used in the presence of pain or vice-versa will fail resulting in the failure of the assistive device for the user
- Frequency-domain features of fNIRS provide high accuracy results for classification of mental arithmetic tasks, but are not immune to the presence of pain
- Additionally, our results indicated that features extracted from both the PF and motor cortices collectively yield better accuracy results as opposed to using features extracted from these areas individually
- The results of this study emphasize the significance of considering pain conditions in the development of BCI algorithms for assistive devices
- Future work will involve identifying features that are immune to the presence of pain, so that the BCI can perform as intended irrespective of the presence of pain



Thank You!