Analysis of the Impact of the Presence of Physical Pain in fNIRS-based BCI Systems

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Outline

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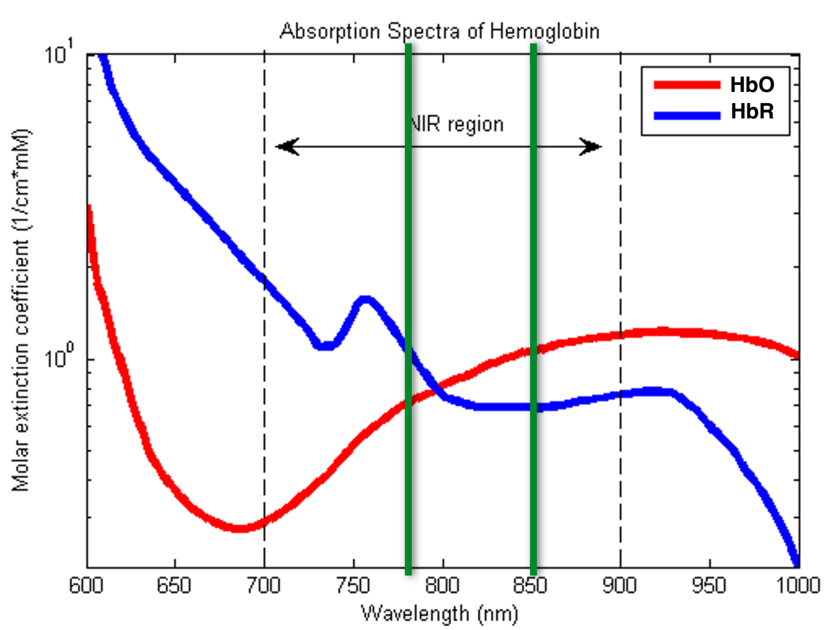
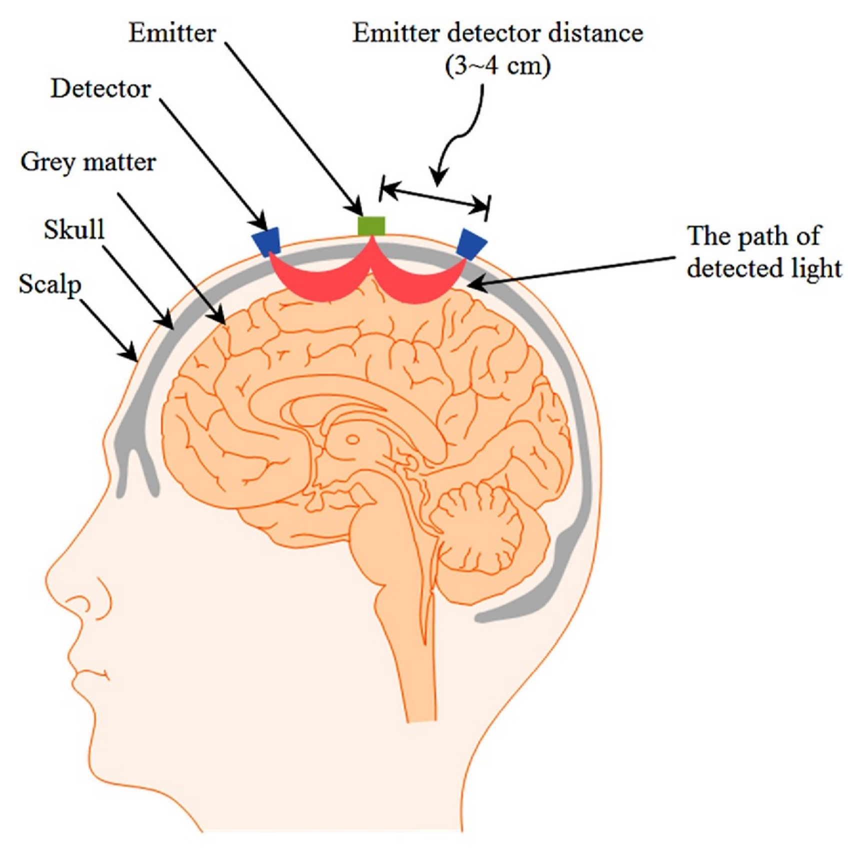
- **Introduction**
  - Background
  - Motivation
- **Methods**
  - Experimental Design
  - Analysis
- **Results**
- **Conclusions**

Background

- **functional Near Infrared Spectroscopy (fNIRS)**
  – Non-invasive neuroimaging technique that measures brain activity via its vascular response
  – Brain activation causes changes in the concentration of Oxy hemoglobin **[HbO]** and Deoxy hemoglobin **[HbR]**



[1]



[2]

modified Beer Lambert Law

$$\Delta c_{HbO} = \frac{\alpha_{HbR}^{\lambda_1}\frac{\Delta A^{\lambda_2}}{L^{\lambda_2}} - \alpha_{HbR}^{\lambda_2}\frac{\Delta A^{\lambda_1}}{L^{\lambda_1}}}{\alpha_{HbR}^{\lambda_1}\alpha_{HbO}^{\lambda_2} - \alpha_{HbR}^{\lambda_2}\alpha_{HbO}^{\lambda_1}}$$

$$\Delta c_{HbR} = \frac{\alpha_{HbO}^{\lambda_1}\frac{\Delta A^{\lambda_2}}{L^{\lambda_2}} - \alpha_{HbO}^{\lambda_2}\frac{\Delta A^{\lambda_1}}{L^{\lambda_1}}}{\alpha_{HbO}^{\lambda_1}\alpha_{HbR}^{\lambda_2} - \alpha_{HbO}^{\lambda_2}\alpha_{HbR}^{\lambda_1}}$$

1. M. Abtahi, et al. "Hand Motion Detection in fNIRS Neuroimaging Data." *Healthcare*. vol. 5, no. 2, 2017.
2. N. Naseer, et al. "fNIRS-based brain-computer interfaces: a review", *Frontiers in human* neuroscience, vol. 9, pp. 3, 2015.

Background

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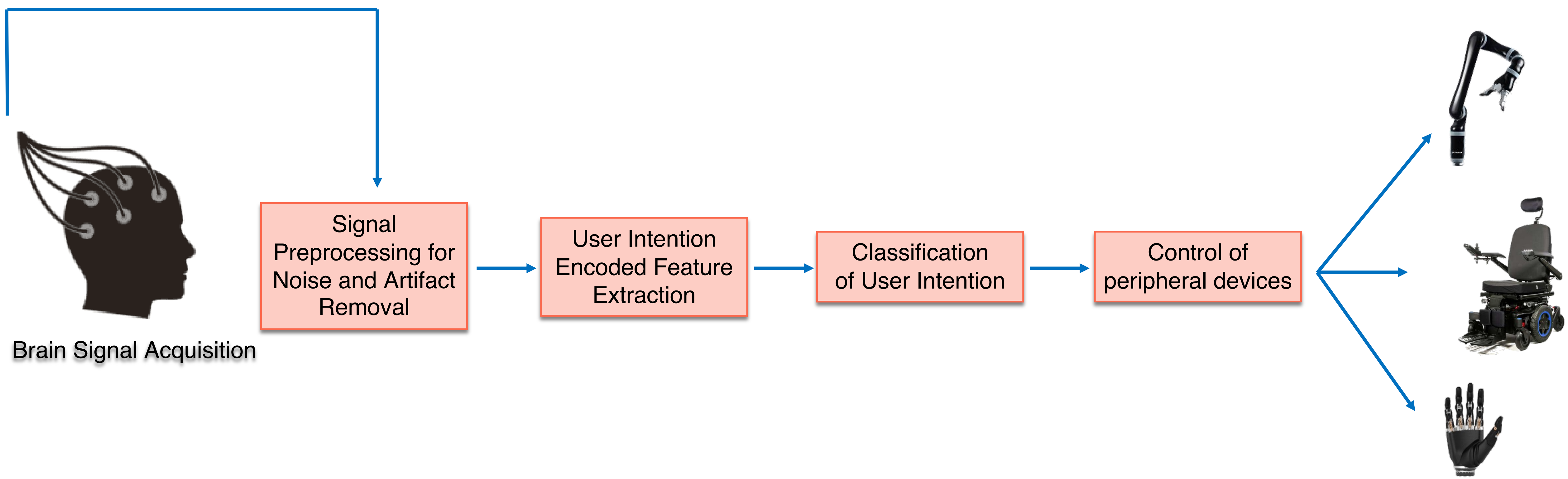
- **Brain Computer Interface (BCI)**
  - Enables control of peripheral devices using signals acquired from the brain
  - Needs to be trained to respond to the subject’s cortical signal prior to application
  - Key application : Assistive interface for patients with motor and communication disabilities



  - fNIRS-based BCIs – use fNIRS technology for brain signal acquisition

Motivation

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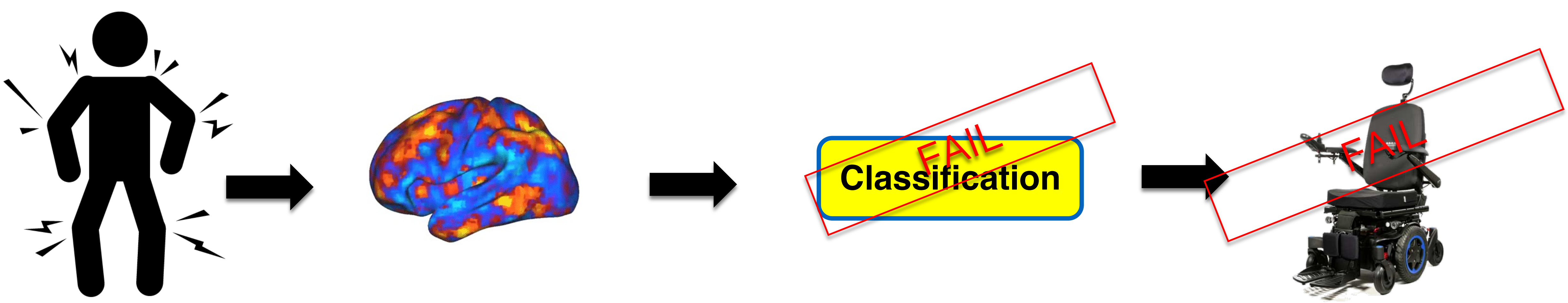
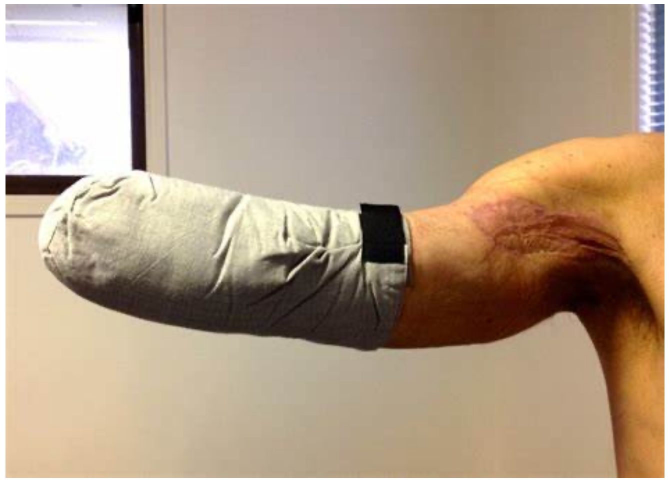
- **Most BCI Users Are Patients Who Experience Physical Pain**
  - Often, pain is prevalent in patients with motor disabilities
  - Pain is expected to impact cortical activity related to the task at hand [3]
  - This in turn would impact the BCI performance potentially resulting in failure of assistive devices



3. D. A. Seminowicz and M. Moayedi, “The dorsolateral prefrontal cortex in acute and chronic pain,” The Journal of Pain, vol. 18, no. 9, pp. 1027–1035, 2017.

Motivation

- **Physical Pain – 3 types**
  - Transient pain
    - Fleeting in nature
  - Acute pain
    - Has a sudden unpredictable onset
    - Higher magnitude and duration than transient pain
    - Caused by injury to local tissue
  - Chronic pain
    - Longest duration
    - Caused by prolonging conditions
    - Possible habituation
  - Among these, acute pain is expected to have more impact on the BCI performance due to its unpredictable nature



Motivation

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- **Goals of This Study**
  - Analyze the impact of the presence of physical pain on mental task classification accuracy of fNIRS-based BCIs using deep learning classifier
  - For further analysis, perform multi-label classification to detect the presence of pain and classify mental tasks simultaneously
  - Propose a strategy to mitigate the negative impact of presence of pain on the BCI performance

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Experimental Design

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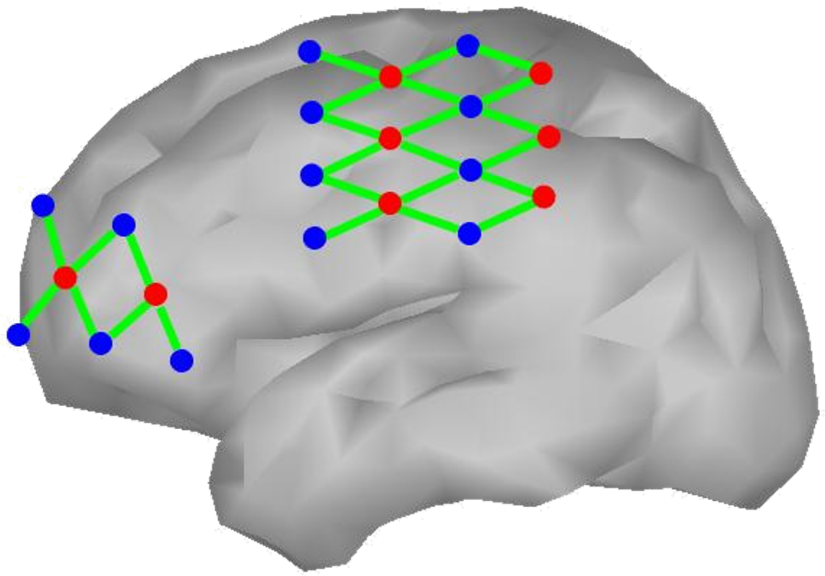
- **fNIRS Recordings**
  - Experimental setup for data collection : NIRx system (sampling rate: 10.41 Hz)
  - Channels:
    - number: 50 (16 sources and 24 detectors)
    - location: prefrontal and motor cortices

NIRx system



Channel configuration

Experimental Design

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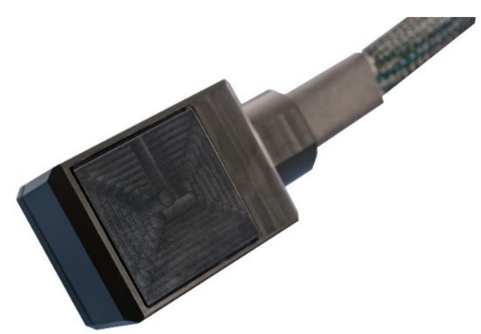
- **Pain Stimulation**
  - TSA-II Medoc System
  - 30 × 30 mm standard thermode
  - Painful stimuli on dorsum of left hand

TSA-II system.



Standard thermode

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

Experimental Design

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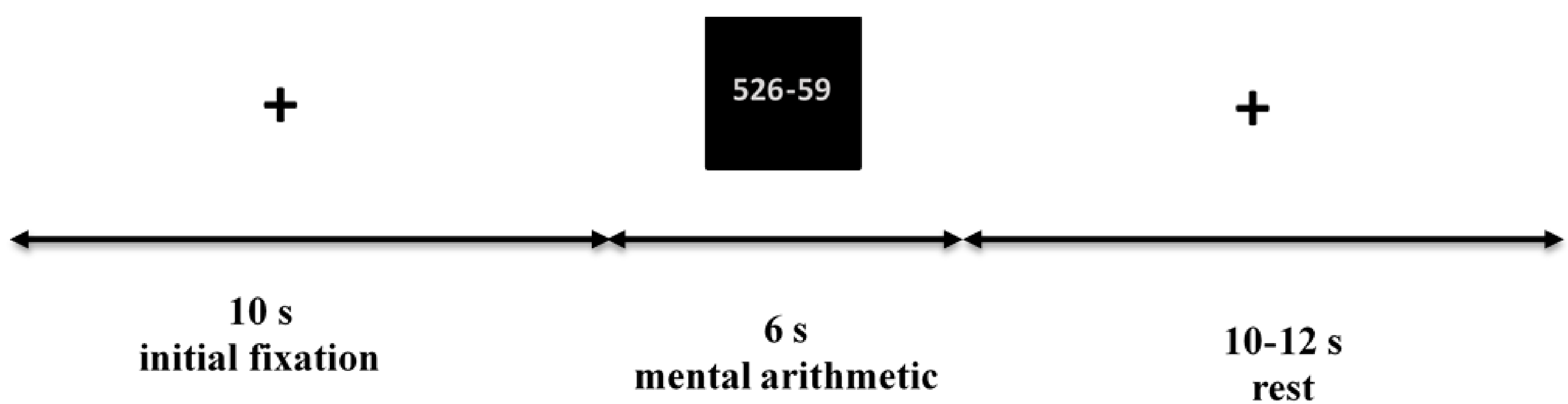
- **Experimental Paradigm**
  - 3 healthy right-handed subjects
  - 5 no-pain and 5 pain blocks in random order
  - 2 classes of mental arithmetic tasks
    - mental subtraction
    - mental back counting
  - Pain inducing stimulus temperature was used for pain blocks and baseline temperature (32℃) for no-pain blocks
  - 65 trials of each task were recorded under pain and no-pain conditions



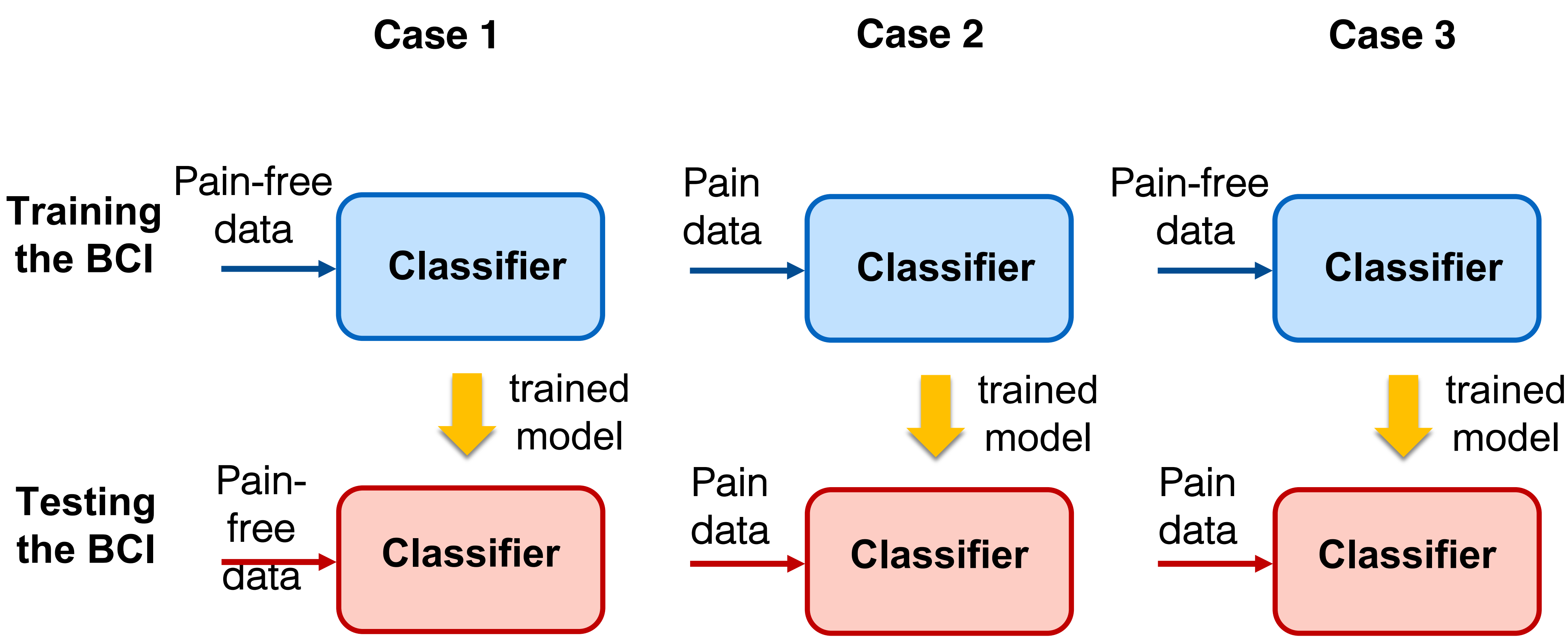
Visual illustration of a single trial.

Analysis

- **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])

Analysis

- **Three Cases of Training and Testing the BCI Classifier Are Considered To Study The Impact of Pain**



Analysis

- **Multi-Label Classification of the Two Tasks**
  - During classification, a data sample can belong to more than one label at a time
  - Multi-label classification schema :

TASK DATA	PAIN LABEL	TASK LABEL
SN	0	0
CN	0	1
SW	1	0
CW	1	1

  - Pain label : No pain condition is labelled 0 and with pain condition is labelled 1
  - Task label : Subtraction task is labelled 0 and counting task is labelled 1

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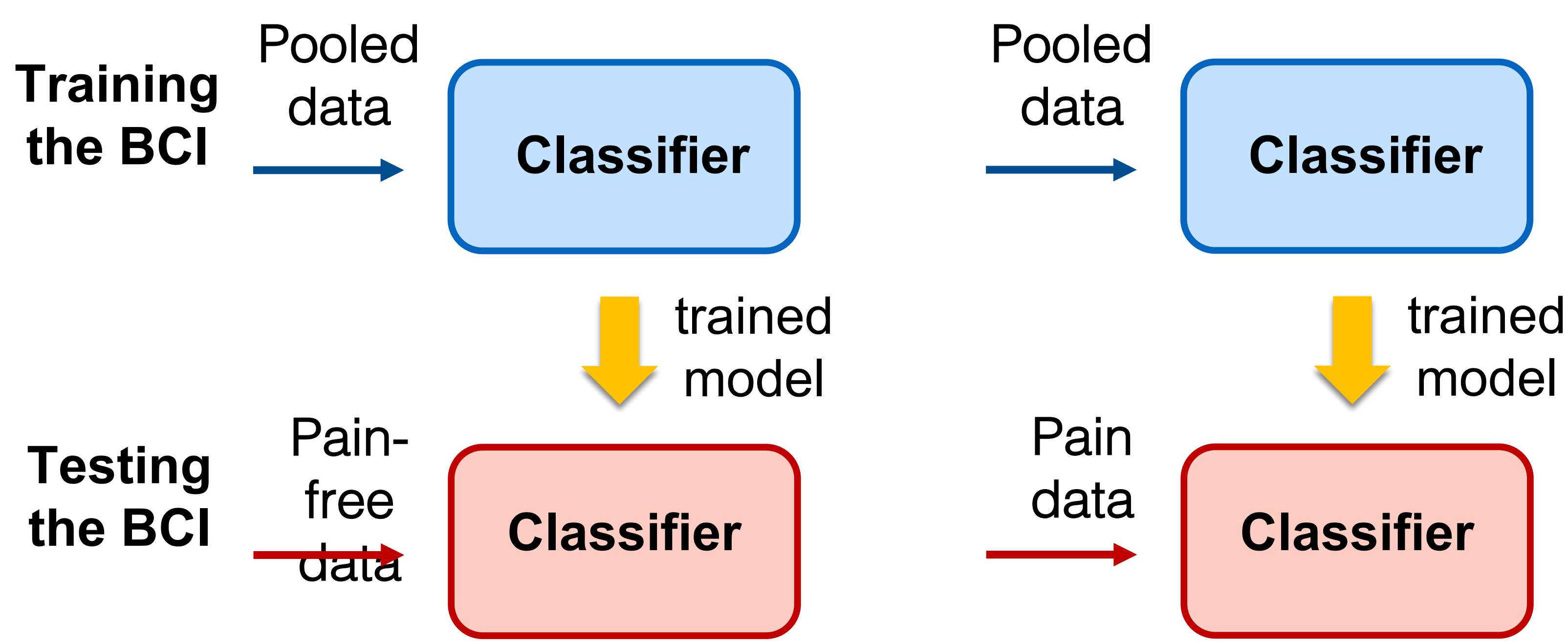
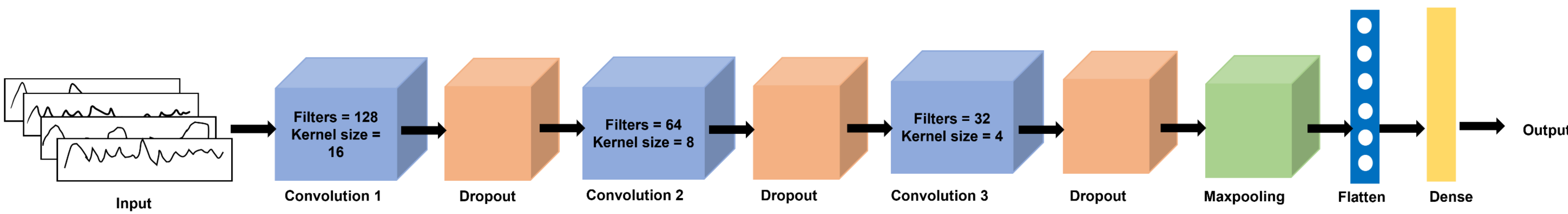
- **Mitigation Strategy**
  - Train the BCI classifier on cortical signals of tasks obtained both in the presence and absence of pain
  - Enables the BCI to learn the cortical signatures of pain along with that of the task during training



Analysis

- **Classifier for the BCI**
  - Deep learning algorithm, convolutional neural network (CNN) was used for classification
  - Same architecture of CNN was used for task classification, multi-label classification and mitigation strategy



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Results

- **Task Classification Results For 3 Cases Of Training And Testing CNN Classifier**
  - Presence of pain impacts classification accuracy and lowers the accuracy to the chance levels

	Case 1 Train (no-pain) Test (no-pain)	**Case 2 Train (pain) Test (pain)**	**Case 3 Train (no-pain) Test (pain)**
Subject 1	92.76± 2.13	90.45± 1.60	52.14± 2.68
Subject 2	92.97± 1.52	93.59± 2.04	49.42± 1.56
Subject 3	95.17± 0.81	93.61± 1.30	59.19± 2.18
AVERAGE	**93.63± 1.48**	**92.55± 1.65**	**53.58±2.15**

Results

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- **Multi-Label Classification Results for CNN Classifier**
  - Metrics : Hamming loss and micro-averaged F1 score
  - Hamming loss measures how well the classifier can make correct prediction on both the presence of pain and the task identification, simultaneously
  - Micro-averaged F1 score for pain identification represents the accuracy with which no pain and pain conditions are identified, while performing the tasks
  - Micro-averaged F1 score for task identification represents the accuracy with which tasks are identified, in the presence or absence of pain

	NP Data			WP Data		
	Hamming Loss	Micro-F1-pain	Micro-F1-Task	Hamming Loss	Micro-F1-pain	Micro-F1-Task
Subject 1	0.15	0.77	0.93	0.24	0.77	0.76
Subject 2	0.048	0.95	0.95	0.19	0.82	0.81
Subject 3	0.048	0.95	0.96	0.15	0.83	0.87
AVERAGE	**0.083**	**0.89**	**0.95**	**0.19**	**0.80**	**0.81**

Results

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- **Mitigation Strategy Results using CNN Classifier**

  – Pooled data training method is used to mitigate the negative impact of the presence of pain on BCI performance

	NP Data	WP Data
Subject 1	91.86± 2.44	79.53± 3.59
Subject 2	95.88± 1.48	82.92± 2.42
Subject 3	96.20± 1.28	88.55± 2.0
AVERAGE	**94.64± 1.73**	**83.67± 2.67**

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Conclusions

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- The CNN classifier for a fNIRS-based BCI provides a reliable way for classification of mental tasks with greater than 90% accuracy, but, when trained on pain-free data and used in the presence of pain , it performed poorly

- For further analysis, we performed multi-label classification. The hamming loss and micro-averaged F1 score metrics for this classification were better for NP data as compared to WP data

- Finally, to remedy the impact of pain, it was shown that the model can be trained collectively on task data obtained both in the presence and the absence of pain

- In conclusion, it is of great importance to consider the presence of pain prior to adapting BCIs for assistive systems

- Future work will explore advanced methods to mitigate the negative impact of pain on the BCI performance

Thank You!

Questions?