Neural mechanisms in processing of emotion in real and virtual faces

A functional near-infrared spectroscopy (fNIRS) study

Dylan Rapanan

March 5, 2025

Task Paradigm

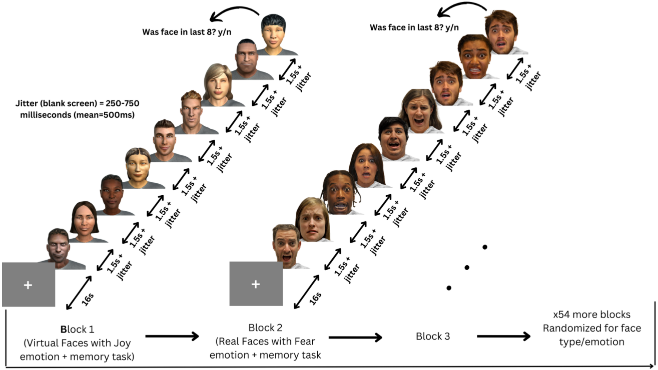

Figure 1: Participants viewed 56 blocks of 8 faces (4 male, 4 female) from two sets: real (RADIATE) and virtual (UIBVFED). Each face displayed one of 7 emotions (anger, disgust, fear, happiness, sadness, surprise, neutral)

fNIRS Montage

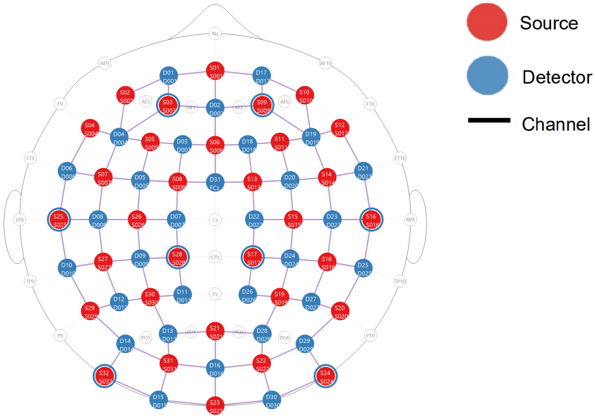

Figure 2: High density 32x32 fNIRS probe layout with 206 channels. fNIRS data recorded using two NIRSport2 systems with sampling rate: 6.105 Hz at wavelengths: 760 *nm* and 850 *nm*.

Signal Quality Metrics

- **Scalp Coupling Index (SCI):**
  - Calculated as the zero-lag cross-correlation between the optical density (OD) signals at two wavelengths.
  - A high SCI value (> 0.7) indicates strong synchronization of cardiac pulsations between the two wavelengths, suggesting good optode-scalp contact.
- **Peak Spectral Power (PSP):**
  - Measures the amplitude of the most prominent frequency component within a specific range, focusing on the cardiac pulsation.
  - A higher PSP value (> 0.1) indicates stronger cardiac signal, correlating with better optode-scalp contact.

Signal Quality by Participant

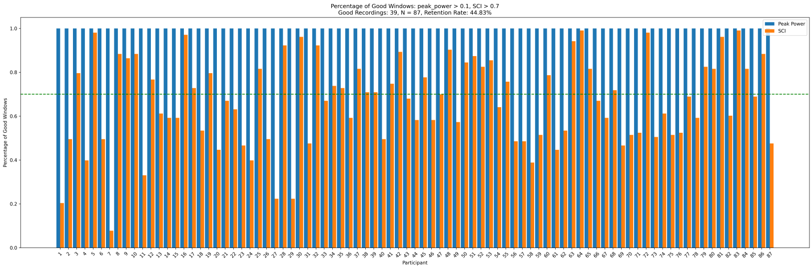

Figure 3: PSP and (SCI) were calculated for 5s sliding windows for each channel for each participant. The dotted green line represents the 70% threshold for good windows.

- If $>$ 70% of the windows in a channel were good, the channel was deemed good.
- If $>$ 70% of the channels in a participant were good, the participant was deemed good.
- 39/87 participants are currently deemed good.

Signal Quality by Channel

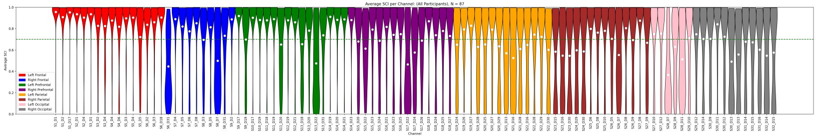

Figure 4: Average SCI for each channel across all participants. The channels are color coded by brain region. The wider the line, the more participants had a SCI value in that range.

- We can see that the channels towards the back of the head tend to have lower SCI values (this may be because people have lots of hair at the back of their head).
- There are a select few channels that have low SCI values across all participants.

General Linear Model (GLM) Analysis

- **Purpose:** GLM's are used to understand the relationship between 1+ independent variables and a dependent variable.
- **Design Matrix:**
  - It encodes the timing + duration of the conditions.
  - Each stimulus is convolved with a Hemodynamic Response Function (HRF) to model the expected brain response.
  - This transforms the stimulus onsets into a predictor that mimics the typical shape of the haemodynamic response.

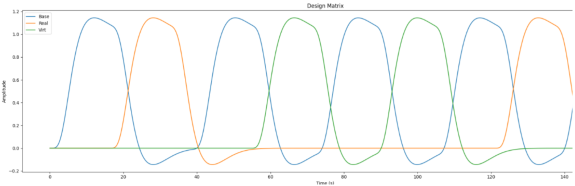

Figure 5: Design matrix (face type) for a single participant (first 150s). Each condition is represented by a different color and represents the onset of a block. The HRF used here is 'spm' (Statistical Parametric Mapping).

General Linear Model (GLM) Analysis

- **GLM Estimation:**
  - The model fits the observed signal as a linear combination of the predictors in the design matrix:

    $$\text{Observed Signal} = \theta_1 \times \text{Predictor}_1 + \cdots + \theta_n \times \text{Predictor}_n + \epsilon$$

    $\theta_1, \theta_2, \ldots, \theta_n$ are the coefficients the model estimates, and ϵ is the error term (noise/unexplained variance).
  - It then applies a fitting algorithm (Ordinary Least Squares) to find the best set of θ's that minimizes the difference between the predicted and actual signals.
  - The θ's indicate the strength of the brain's response to each experimental condition.

GLM Analysis

- **Group-Level Analysis:** $\theta \sim -1 + \text{ROI} : \text{Condition} : \text{Chroma}$
  - This mixed effects model estimates separate coefficients (θ's) for each combination of Region of Interest (ROI), condition, and channel type without a global intercept.
  - Group by participant for variability between subjects.

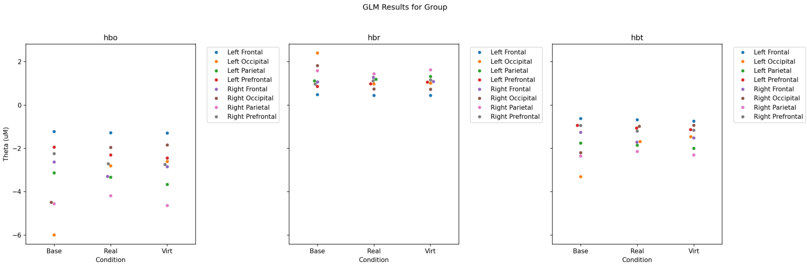

Figure 6: Swarm plots display θ's across conditions/ROIs for each channel type. Higher θ values indicate stronger responses.

GLM Contrasts

- **Contrasts:**
  - Contrasts between pairs of conditions (i.e. `Joy - Fear`) are defined by subtracting corresponding regressors.
  - This highlights the differences in haemodynamic responses under the combinations of conditions.

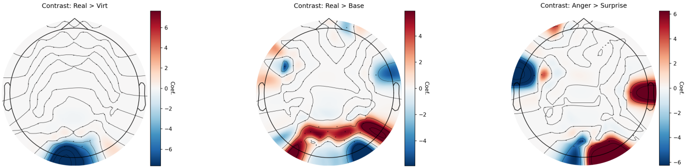

Figure 7: Contrast maps (Hbo) for Real vs. Virtual (left), Real vs. Baseline (middle), and Anger vs. Surprise (right).

- Only channels with $P < |z|$ less than 0.05 are displayed, indicating a significant difference in Hbo.

Event Related Potentials (ERPs)

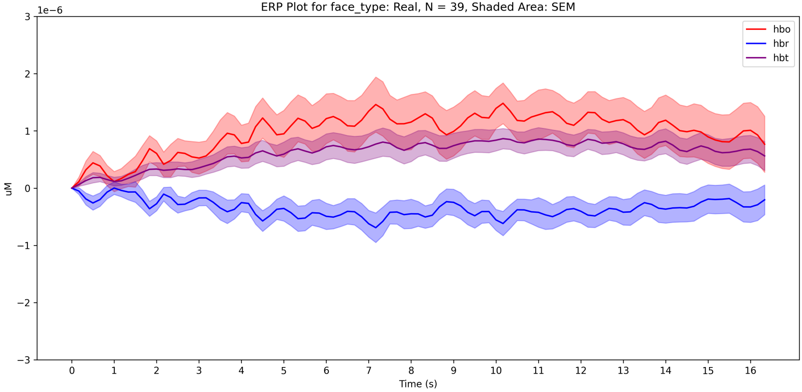

Figure 8: ERP for real face epochs across all channels. The x-axis represents time in seconds (s) and the y-axis represents the ΔHbo/Hbr/Hbt in micromolars (μM).

- The shaded region is the standard error of the mean: $\frac{\sigma}{\sqrt{n}}$.

ERP Differences

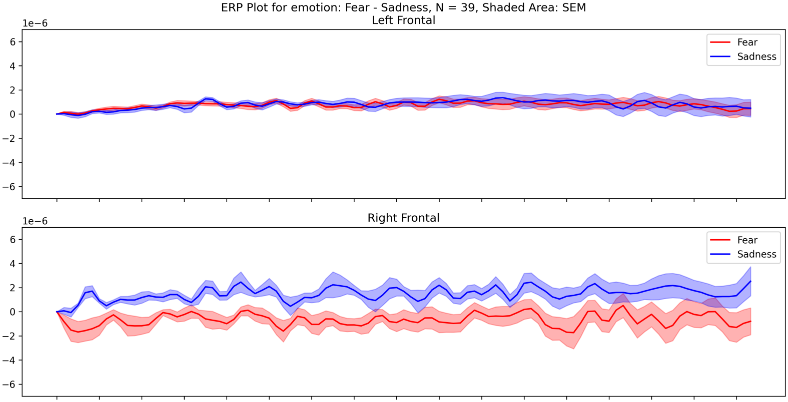

Figure 9: ERP difference in Hbo between fear and sadness for Left/Right frontal regions.

ERP Differences

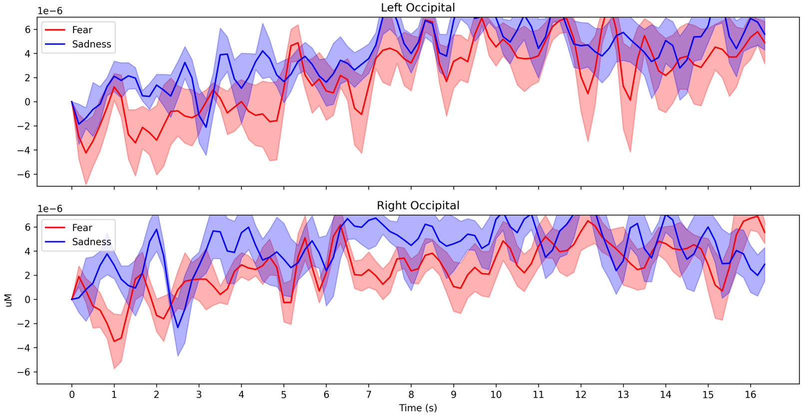

Figure 10: ERP difference in Hbo between fear and sadness for Left/Right occipital regions.

Connectivity Analysis Methodology

- **Connectivity Analysis:** We analyze the relationship between channels to understand how different regions of the brain communicate.
- **Parameters:**
  - # Coherence as the connectivity metric:
    - `method = "coh"`
  - # CWT with Morlet wavelets for time-frequency analysis:
    - `con_mode = "cwt_morlet"`
  - # Analyze frequencies ranging from 0.01 Hz to 0.5 Hz:
    - `cwt_freqs = np.linspace(0.01, 0.5, 10)`
  - # Use 1 cycle per frequency for wavelet transformation:
    - `cwt_n_cycles = 1`
  - # Average connectivity matrices across frequencies:
    - `faverage = True`

Connectivity Analysis

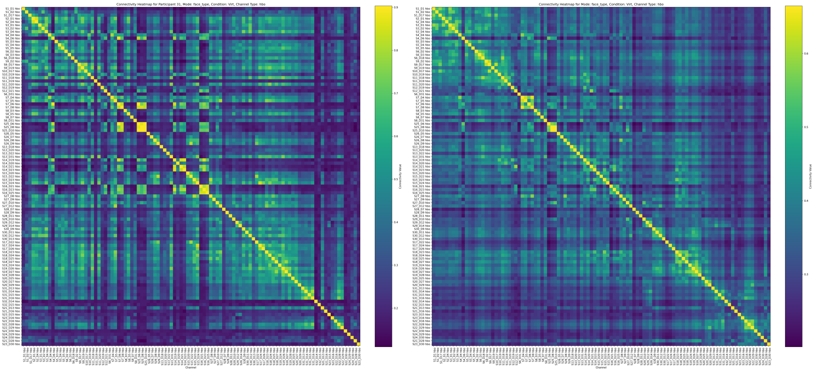

Figure 11: Virtual face connectivity heatmaps for a single participant (left) and the average across all participants (right). The x-axis/y-axis represent the channel. A brighter color $\implies$ higher connectivity strength.

- The averaged heatmap has a more washed out distribution.

Connectivity Chord Plots

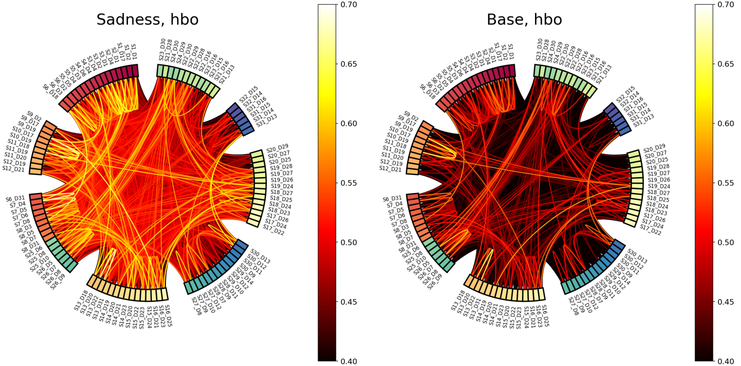

Figure 12: Chord plot of connectivity between channels for sadness (left) and baseline (right) conditions. Brighter lines represent higher connectivity strength.

- Connections across the middle of the plot indicate connectivity across far apart regions of the brain.

Connectivity Group Level T-Tests Chord Plots

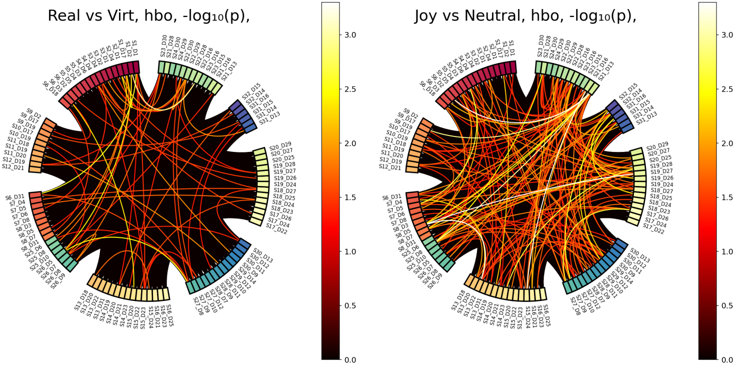

Figure 13: Paired t-tests were conducted for each unique pair of conditions (i.e. Real vs. Virtual (left) and Joy vs. Neutral (right)). *p*-values were computed for each channel pair across participants.

- False Discovery Rate (FDR) correction was applied, which controls the expected proportion of false positives among all significant results when conducting multiple hypothesis tests.

Decoding Analysis Methodology

- **Data Preprocessing:**
  - **Scaler:** Scales each channel to zero mean and unit variance.
  - **Vectorizer:** Flattens data into a 2D feature matrix.
  - **Model:** Pick the classifier (e.g., `RandomForestClassifier`).
- **Cross-Validation:**
  - We perform 5-fold cross-validation, where data is split into 5 folds, preserving the class distribution (stratified splitting).
- **Scoring:**
  - **ROC-AUC Score:** A single metric that quantifies a model's ability to distinguish between classes by calculating the area under the ROC curve, where 1.0 indicates perfect discrimination and 0.5 represents random guessing.
  - Each fold is evaluated using the ROC-AUC score with the one-vs-rest (OVR) approach for multiclass evaluation.
- **Aggregation:**
  - Mean of the scores across folds are computed for each participant, providing a robust estimate of model performance and its variability.

Decoding Analysis Results

Model Scores (ROC-AUC %)

Model	face_type	emotion
GaussianNB	73.21	56.16
HistGradientBoostingClassifier	81.22	73.3
KNeighborsClassifier	69.75	58.24
LGBMClassifier	81.34	**73.39**
LogisticRegression	78.17	67.3
MLPClassifier	77.4	65.66
QuadraticDiscriminantAnalysis	51.09	50.15
RandomForestClassifier	**83.46**	72.36

Figure 14: Spatio-temporal classification performance of multiple machine learning models across conditions. For each model, recordings were preprocessed via scaling and vectorization. The average ROC-AUC scores were computed using five-fold cross-validation over all recordings.

- The `RandomForestClassifier` model performed the best in identifying the face type, while the `LGBMClassifier` model performed the best in identifying the emotion.