Classification of First-Episode Psychosis (FEP) Patients with Live Face Processing

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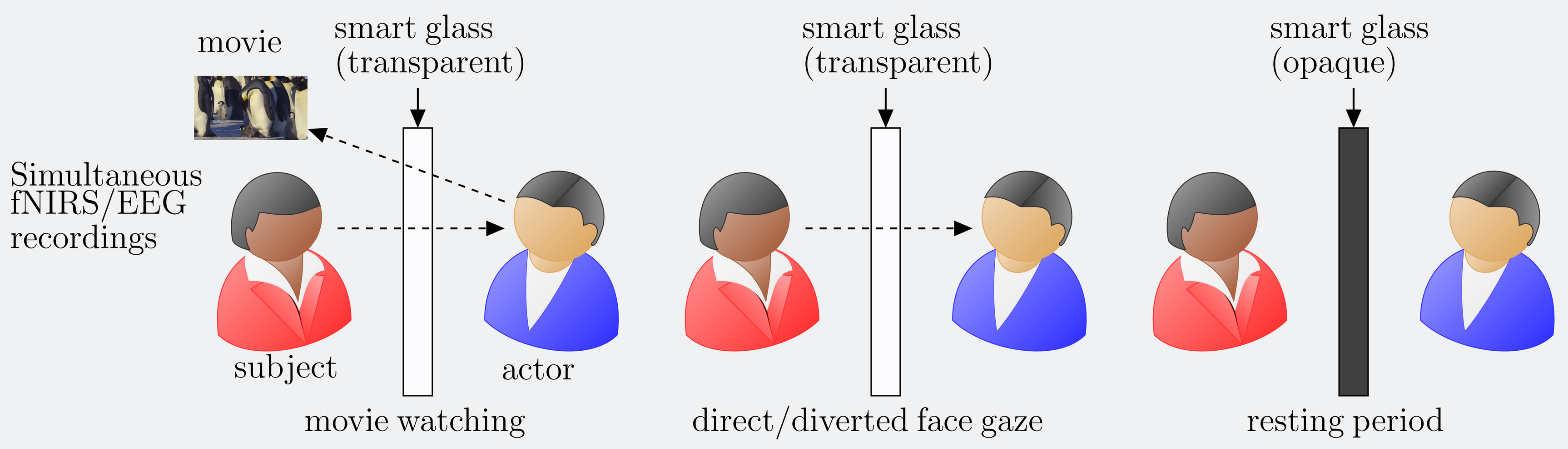
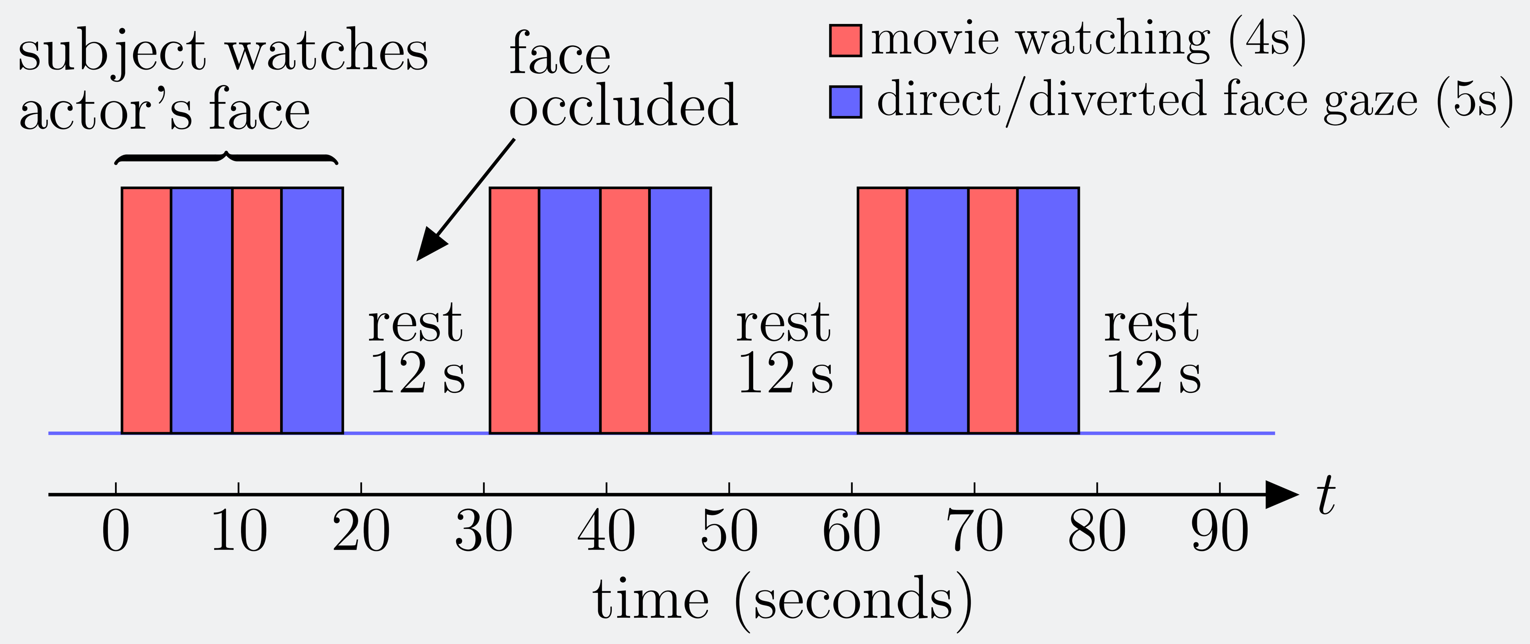
Abstract

- A deep learning method for classifying first-episode psychosis (FEP) patients from neural and behavioral recordings during a novel live face-to-face interaction paradigm
- Recurrent encoder-decoder networks to learn (joint) low-dimensional representations of multimodal brain imaging and behavioral data, e.g. fNIRS, EEG, and facial expressions
- We show that these (joint) learned representations improve FEP classification and also can predict specific GAF role scores (measure of functioning)

Experimental Setup

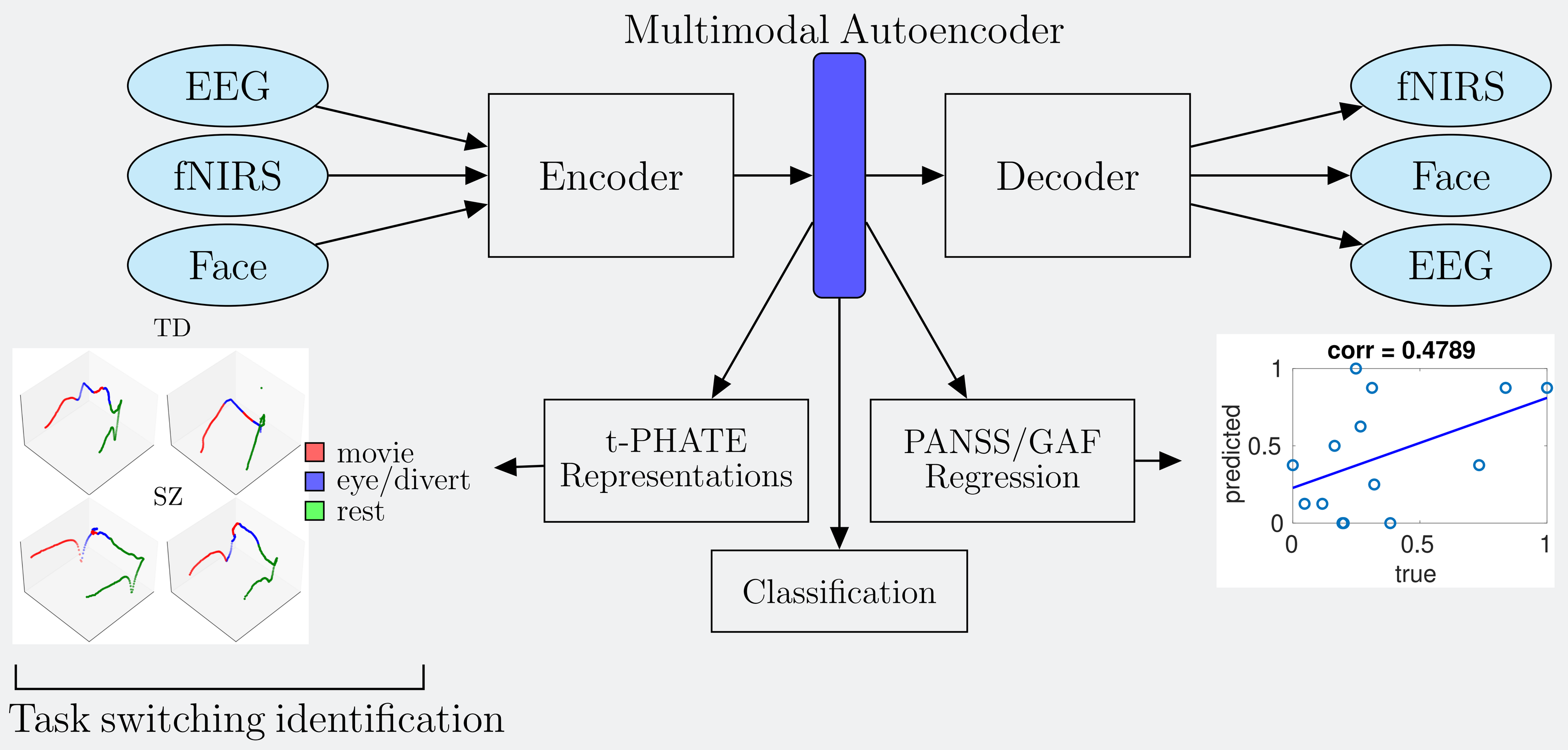
"Live interactive neuroscience" approach [1]

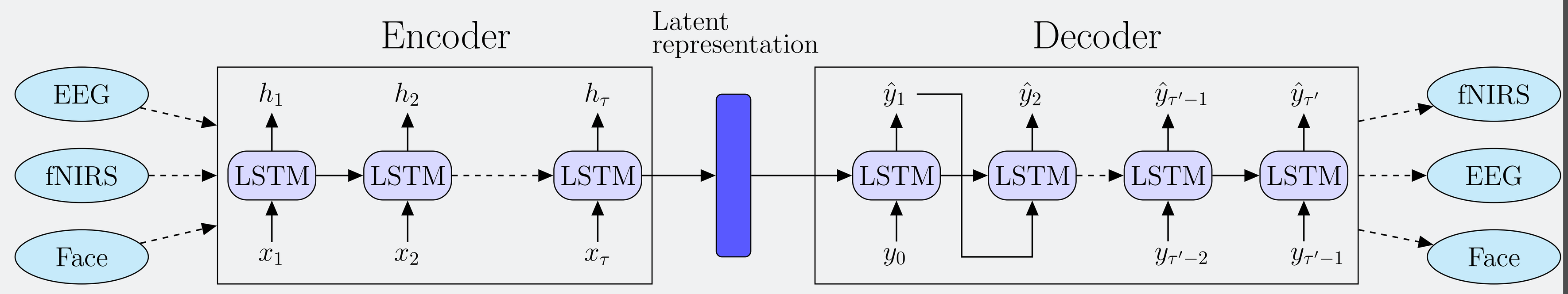




- 19 typically developed (TD) individuals and 14 FEP patients
- Functional brain responses are acquired with Shimadzu LABNIRS (134 channels) and EEG (32 channels) along with facial expression recordings
- 24 blocks (each of 30 seconds) of brain activity where the actor is stimulated by different emotionally valenced videos

Method



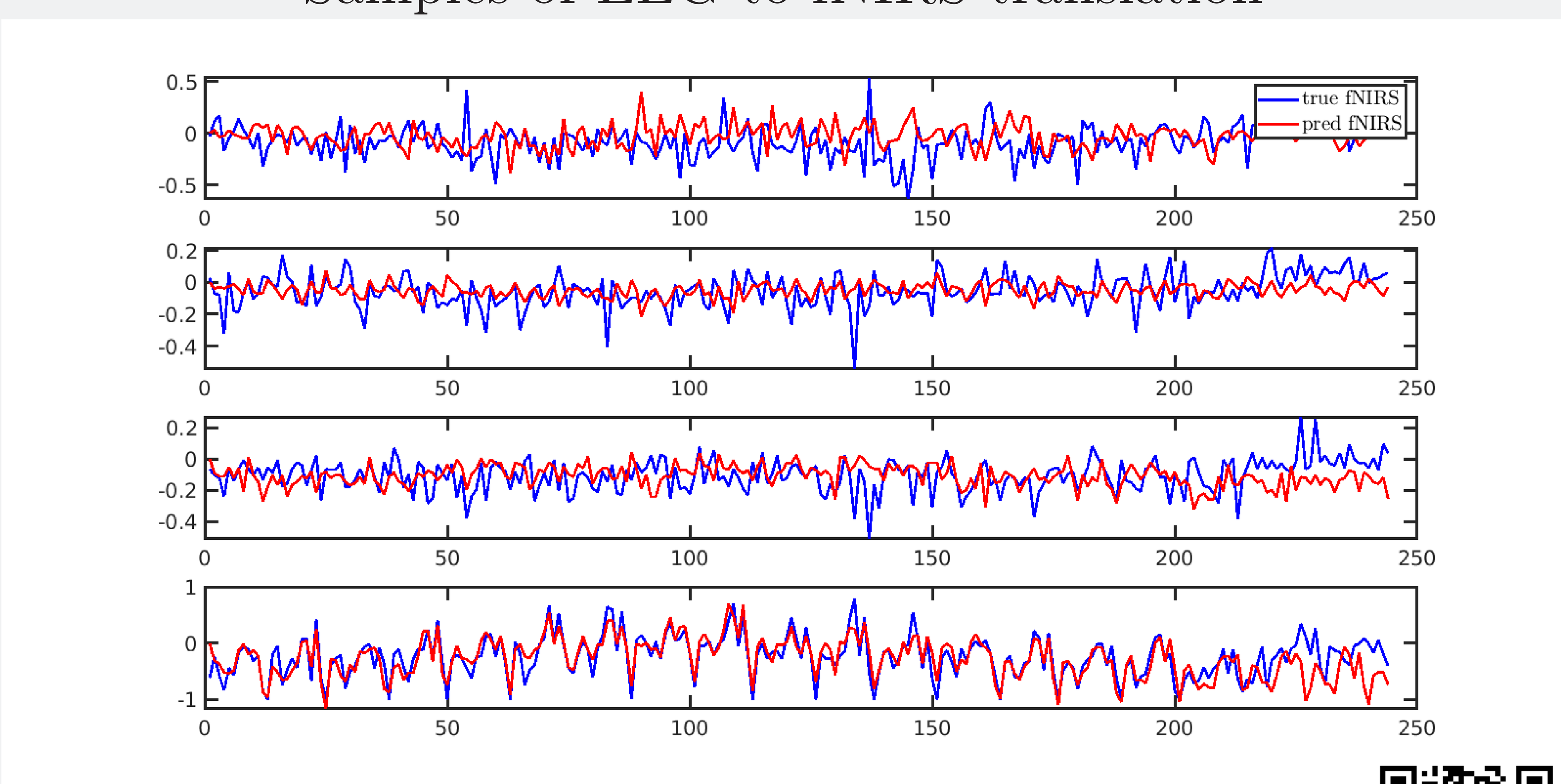


- The action units (AU) of facial expressions were computed using OpenFace [2]
- The encoder and decoder framework consists of multiple long short-term memory (LSTM) layers to learn latent representations (128 dimensional) from multiple modalities including fNIRS, EEG, and facial expressions.
- The learned representations are further fed to a multilayer perceptron (MLP) for classification in trials and subjects withheld during training.
- We utilize a nonlinear dimensionality reduction method, tPHATE [3], to visualize the learned embeddings in 3-D

Results

- Incorporating joint representations from fNIRS and EEG (theta band) data **enhances accuracy** to 88%
- The classification accuracy achieved using fNIRS data on withheld subject blocks is 85%, outperforming traditional support vector machine (SVM) accuracy of 71% and stand-alone MLP accuracy of 67%
- The correlation coefficient between predicted scores and true GAF role scores is computed at 0.4789
- Visualizing the learned embeddings in 3-D space using tPHATE enables the identification of task switching times

Samples of EEG to fNIRS translation



To download the poster and more information →

References

[1] Hirsch et al. Neural correlates of eye contact and social function in autism spectrum disorder. *Plos one*, 2022.

[2] Baltrusaitis et al. OpenFace 2.0: facial behavior analysis toolkit. In *2018 13th IEEE International Conference on Automatic Face Gesture Recognition*, 2018.

[3] Busch et al. Multi-view manifold learning of human brain-state trajectories. *Nature computational science*, 2023.

[4] Zhang et al. SVM prediction of individual ADOS scores based on neural responses during live eye-to-eye contact. *Scientific Reports*, 2024.

[5] De Miras et al. Schizophrenia classification using machine learning on resting state EEG signal. *Biomedical Signal Processing and Control*, 2023.

Acknowledgements

Participants provided written informed consent in accordance with guidelines approved by the Yale University Human Investigation Committee (HIC #1501015178). NIH NIMH R01MH111629 (JH); NIH NIMH R01MH107573 (JH); NIH NIMH R01 MH119430 (JH); Pfeiffer, Gustavus and Louise Research Foundation. Findings are solely the responsibility of authors and do not represent official views of NIH