Affective state detection during fatiguing motor tasks in the elderly using brain hemodynamics

Rohith Karthikeyan, Abedallah Al Kader, Anthony McDonald, and Ranjana K. Mehta

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Introduction

The goal for this investigation is centered on building a robust classification scheme for detecting stress during a fatiguing motor task in an aging population.

- **Rationale:** Affective inference is a challenging problem in the elderly, when relying on biomarkers that are limited by confounding pathophysiological conditions and demographic variables
- **Hypothesis:** Personalized machine learning workflows that operationalize functional near-infrared spectroscopy are robust and could overcome confounds in stress manifestation
- **Approach:** We take a supervised learning approach, with observations labeled based on the experiment phase, as validated using salivary cortisol measures taken during the experiment protocol

Methods and protocol

We recruited **59** participants (30 female) from the Bryan-College Station community, who were cast into counterbalanced groups for **hand-grip** and **knee-extension** stress protocols, on separate days.

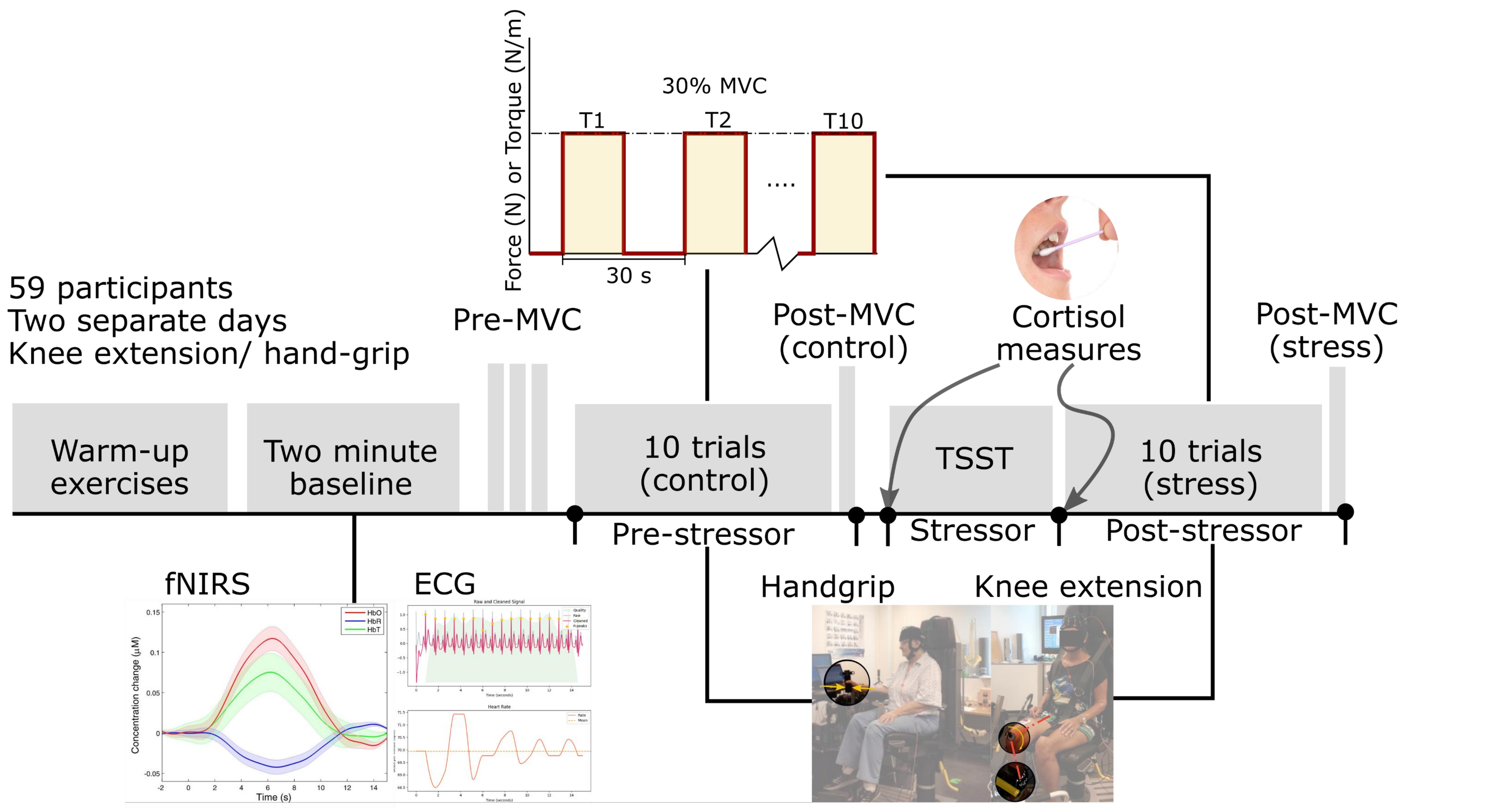

Fig. 2: **(a)** Schematic representation of the experiment protocol for hand grip and knee-extension experiments. Stress was induced by the Triers social-stress test, with cortisol samples taken before and after the stressor block serving as ground truth indicators for affect state.

Signal processing pipeline

The raw fNIRS signal (1000 Hz) and performance data (block-wise) are recorded during the experiment and subject to an exhaustive feature extraction workflow.

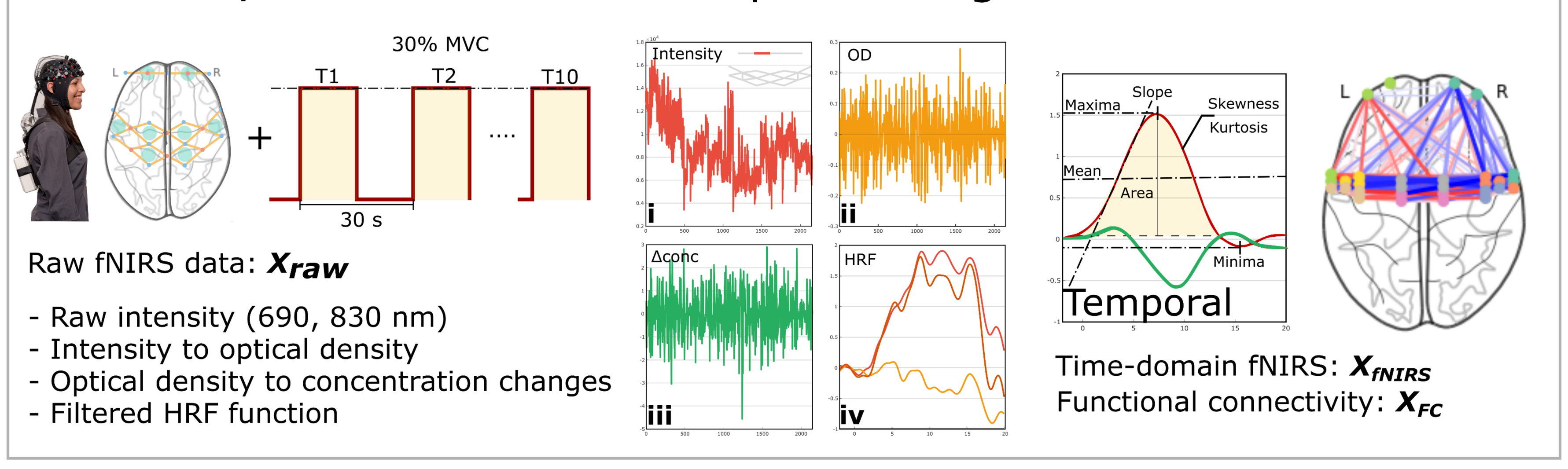

Fig. 2: Raw fNIRS data is segmented, filtered, and subject to a feature extraction pipeline that generates 10 temporal features for each channel, and signal type. We also generate pairwise functional connectivity features for each channel.

1. A sliding window is applied, epoch size: *15s* , *50%* overlap
2. fNIRS features are min-max normalized across each participant
3. Cortisol measures serve as ground truth labels for stress conditions

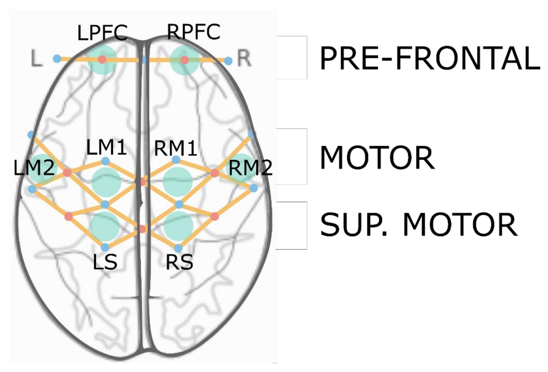

Fig. 3: fNIRS probe map used in the study

Stress detection workflow

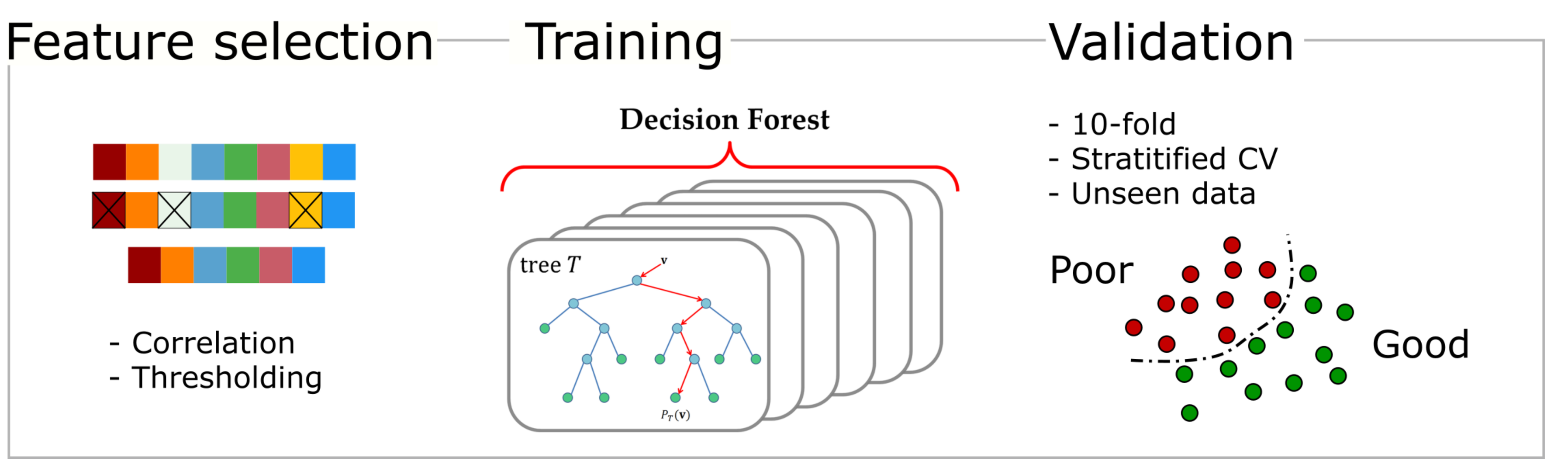

Fig. 4: The machine learning workflow used takes a supervised approach where observations are labeled contingent on the phase they are sourced from i.e. pre-stressor: *no stress*, and post-stressor as *stress*. An exhaustive ensemble learning template was built in *scikit-learn 0.23.2* with *10*-fold stratified cross-validation

The Random Forest was among the top performing models with a CV accuracy *of 83.11% (sensitivity of 79%, and specificity of 84%).*

Results and implications

Temporal fNIRS features

		Hand			Knee		
		All	Female	Male	All	Female	Male
Hand	All	0.878±0.005	0.991	0.987	0.456	0.398	0.523
	Female	0.764	0.883±0.004	0.521	0.414	0.328	0.512
	Male	0.766	0.543	0.874±0.004	0.406	0.342	0.478
Knee	All	0.530	0.510	0.552	0.845±0.005	0.975	0.946
	Female	0.526	0.518	0.533	0.797	0.828±0.005	0.574
	Male	0.538	0.515	0.562	0.661	0.369	0.815±0.003

Fig. 5: Table representing stress detection accuracy when using temporal fNIRS features; rows present the training set and columns the test set. An 80-20 split was applied for diagonal elements.

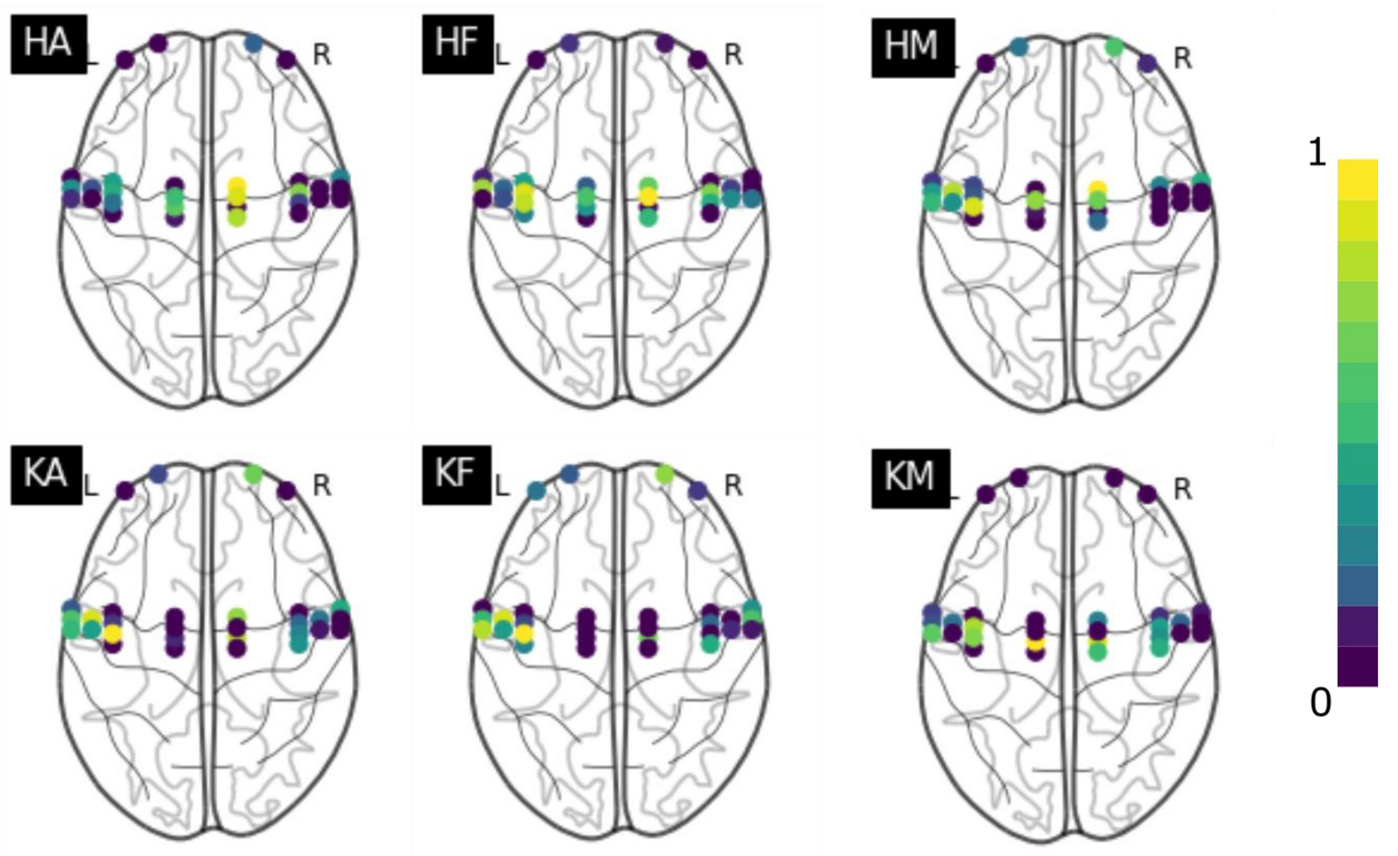

Fig. 6: Brain map indicating the regions of importance based on a permutation importance score for each fNIRS channel. Medial components figure prominently in classifier outcomes on hand data, while ventral components are dominant with knee data. The frontal cortex does not appear to be coherently relevant to classifier outcomes.

Functional connectivity features

		Hand			Knee		
		All	Female	Male	All	Female	Male
Hand	All	0.790±0.004	0.668	0.644	0.462	0.463	0.461
	Female	0.644	0.775±0.003	0.500	0.500	0.488	0.516
	Male	0.590	0.490	0.758±0.005	0.468	0.456	0.481
Knee	All	0.485	0.483	0.488	0.810±0.002	0.824	0.735
	Female	0.487	0.483	0.481	0.764	0.824±0.004	0.725
	Male	0.486	0.483	0.488	0.735	0.823	0.797±0.003

Fig. 7: Table representing stress detection accuracy when using temporal functional connectivity features; rows present the training set and columns the test set. An 80-20 split was applied for diagonal elements.

1. Strong group differences evident in the trained models
2. Models do not generalize well across sexes, and limb type
3. Cortical representations of stress robust to motor task effects
4. Functional connectivity appears to generalize better on knee data

NeuroErgonomics Laboratory
Texas A&M University