Multivariate Analysis of Human Health and Performance in an Acute Spaceflight Simulation

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Aims

1) Identify and classify stress using physiological signals
2) Search for a relationship between sensorimotor performance and physiological health
3) Describe the physiological characteristics of adaptation

Introduction

- Optimal human performance requires proper orchestration of different physiological and psychological systems.
- In the context of extended spaceflight, the ability to perform is crucial to the success of the mission.
- While the health effects of spaceflight are normally studied individually and separately, evidence points to the value of an **integrated approach**[1,2] for looking across different health domains, since performance outcomes are determined by the integration of multiple body systems.
- We propose to use **multivariate analysis techniques** to examine various health and performance measures.
- To test this, we devised an experiment that simulated the **sensorimotor stresses** of spaceflight and collected continuous physiological and performance data from it using various devices.

Fig. 1: Various sensorimotor perturbations and activities done during the experiment that aim to mimic spaceflight.

Fig. 2: The Empatica E4 wristband used to take physiological measures (left), and the Shimmer3 IMU used to measure body acceleration (right).

- 45 healthy subjects performed the experiment. Informed consent was obtained in accordance with IRB regulations.

Experiment Design

- The experiment consists of 3 phases: **unperturbed phase** (seated), **perturbed phase** (standing), and **recovery phase** (seated). Each phase consists of two rounds, with 25 min of copying an article and a 5 min break.
- Perturbations: **prism glasses** to induce vertical skew and **weighted body vest** tuned to 10% of the subject's weight.
- For the duration of the experiment, the following measurements were taken:
  - Heart Rate (HR)
  - Skin Conductance (EDA)
  - Skin Temperature (TEMP)
  - Inter-beat Interval (IBI)
  - Body Motion (arms, torso, head) (ACC)
  - Vertical Ocular Alignment (VAN)
  - Perceived stress level (Likert Scale)
  - Task Completion Time
  - Average typing speed, words per minute, keystroke intervals

Analysis

1. We had two steps to analyze our signals:
   a. **Feature extraction** from signals (Fig. 3-6)
   b. **Stress detection** using classification algorithms like logistic regression and support vector machines

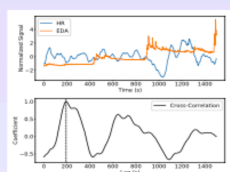

Fig. 3: Demonstration of cross-correlation lag time for HR and EDA signals. Here, the heart rate lags the EDA by 200 seconds.

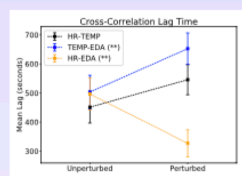

Fig. 4: Mean lag time for pairwise combinations of signals. ** indicates a Mann-Whitney difference with $p < 0.05$.

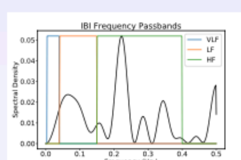

Fig. 5: We integrate over low, high, and very high frequency passbands and compute frequency-domain statistics for the inter-beat interval signal.

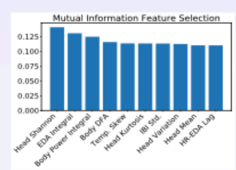

Fig. 6: Selection of best features via mutual information score. These ten features encode the most information about perturbation and stress level.

Results

1. Stress detection (binary classification) with a sensitivity-specificity AUC score of **0.94**, and an accuracy of **85%** on our data (cross-validated)
2. The multivariate approach is superior to isolated methods, with a higher accuracy

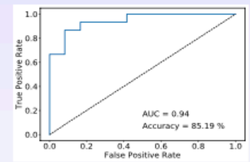

Fig. 7: Receiver-operating characteristic (ROC) curve for our logistic regression classifier.

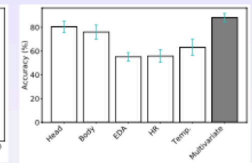

Fig. 8: Comparison of classification accuracy using different isolated signals versus their combined information.

Preliminary Conclusions & Future Work

- We have developed a tool that enables us to predict the perceived stress level of a subject solely from signals collected via a wristband sensor.
- We have shown that multivariate analysis markedly improves classification accuracy.
- We have identified and written over a dozen signal statistics that are powerful at detecting perturbations.
- Currently, we are working on:
  1. Packaging our code into a software tool for all researchers
  2. Studying physiological adaptation to sensorimotor perturbations.
  3. Using known physiological stress responses to predict performance in sensorimotor tasks.

Challenges

1. Which measures accurately identify signals physiologically coupling and decoupling?
2. How can we best analyze and use our performance data (such as keystroke metrics, performance times, etc.)?
3. What other hypotheses can be tested with multivariate physiological data in the context of spaceflight?

References

[1] Chiel, H. J. & Beer, R. D. (1997) Trends in Neurosciences 20, 553–557.
[2] Li, X. et al (2017). PLOS Biology, 15(1).