MULTIVARIATE ANALYSIS OF HUMAN HEALTH AND PERFORMANCE IN EXTENDED SPACEFLIGHT

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ABSTRACT

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 crew survival and to the success of the mission, especially under compromised health conditions. While the health effects of spaceflight are normally studied individually and separately, evidence points towards the value of using an integrated approach[1,2] for looking at different health systems, since performance outcomes are determined by the integration of multiple body systems. Large deviations from baseline in these interactions, such as overly strong or weak coupling of systems, may indicate the onset of or be a symptom of a condition. Thus, investigating the interactions between health systems is as pertinent as investigating health systems individually. Ultimately, development of multivariate analysis techniques to examine various health and performance measures could enable forecasting of patterns in other body systems, better define resiliency, and provide a means to predict decreases in performance levels that could adversely affect mission outcomes.

EXPERIMENT PROTOCOL

The study was divided into five rounds: in the first two the subject was unperturbed, in the next two they were perturbed, and in the last they were unperturbed and in recovery. Baseline measurements were taken during the first two rounds. Perturbations comprised of prism lenses that induced eye misalignment and a weighted vest to induce fatigue, both of which are sensorimotor symptoms that occur during or post-flight. Throughout the experiment, participants were asked to complete a sustained typing task, which was periodically interrupted by a time-to-completion search task. Between trials and perturbations, participants completed a visual alignment test (VAN) while wearing blue/red color filter lenses, and a self-report index of stress (created on a Likert scale). A combination of monitoring technologies were utilized to track physiology, including the E4 wristwatch to record skin temperature, conductance, blood volume pulse, and heart rate and heart rate variability, and Shimmer inertial measurement units to quantify movement.

ANALYSIS AND PREDICTIONS

We applied a host of non-linear techniques to measure the effect of the perturbations on various physiological signals. One technique used was detrended fluctuation analysis (DFA), which provides a measure of the non-linear self-affinity of a signal. Applying the DFA exponent to our data yielded a significant sensitivity (Kruskal-Wallis (KW) $p < 0.05$) to perturbation for several signals, including blood volume pulse (BVP) and acceleration. Recurrence quantification analysis on a joint state space of two signals (such as heart rate and skin temperature), which quantifies non-linear interaction between two signals, also showed significant reaction (KW $p < 0.05$) to perturbation. These parameters were then used to predict the stress score for a subject. Via a multivariate Gaussian-process regression, we achieved a cross-validated accuracy of predicting the score within 2 points on average.

We also explored machine learning techniques to classify our signals. Our continuous signals were windowed, and ~35 statistical features were calculated for each window. A random forest model that performs a binary classification was then used to predict whether each windowed sample was drawn from a stressed or relaxed phase, defined by the median stress score. Each window contained statistics from three signals: heart rate, temperature, and skin conductance. Thus, this model took into account multivariate interactions between the signals. We obtained a cross-validated classification accuracy of 93% on our dataset. Therefore, we have developed a tool that enables us to predict the perceived stress level of a subject solely from physiological signals collected via a wristband. This model is still a work in progress, and we are working on deriving more useful statistics, as well as utilizing other signals like heart rate variability and acceleration, to improve the classification accuracy.

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).