Machine Learning for the Prediction of Autonomic Nervous System Response during Virtual Reality Treatment using Biometric Data

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Abstract

We aim to improve the understanding and clinical management of Canadian Forces service members and veterans suffering concussion, complex pain, and PTSD using machine learning techniques on data collected from virtual reality treatment sessions at The Ottawa Hospital Rehabilitation Centre.
keywords: post-traumatic stress disorder (PTSD), mild traumatic brain injury (mTBI), chronic pain, complex pain, machine learning

1 Introduction

Mild traumatic brain injury (concussion), complex pain, and post-traumatic stress disorder (PTSD) are associated with heightened sympathetic activation of the autonomic nervous system (SAANS, "fight or flight response"). In Canadian Forces members and veterans, these conditions often occur as a triad (polytrauma), posing clinical challenges in their treatment and management. At The Ottawa Hospital Rehabilitation Centre, a key technique for treatment employs a Computer Assisted Rehabilitation Environment (CAREN) facility; allowing patients to experience motion and interact with a virtual environment.

Treatment occurs under the direct supervision of the treating clinician and requires a high degree of experience and training to achieve appropriate patient exposure. Our study aims to capture, analyze and eventually provide "live" feedback to clinicians on patients' SAANS response through minimally intrusive capture and analysis of biometric data that are not typically recorded, using machine learning techniques and cloud computing resources.

2 Methodology

Patients are currently being recruited with a target of 60 patients over the 2 year study. Heart rate, breathing, and movement (acceleration) are captured from the Zephyr Biopatch HP (Medtronic). Time series for 3D motion capture (VICON), force plates under the treadmills, and the configuration of the simulated environment, CAREN hardware and D-Flow software (MotekForce Link), are stored for each session. Clinicians use a tablet-based custom app to record their observations of SAANS signs and symptoms, administer the simulator sickness questionnaire (SSQ), and record comments and common events, all time-stamped and uploaded to the cloud servers (SOSCIP/IBM).

Study clinicians collect data from 3–6 activities lasting 15–300s (typical) over each 1h treatment session. Data are processed to compute features, largely focused on measures of variability. These features are used to (a) develop patient-specific models of pre-treatment baseline, and (b) to capture deviations from these patient-specific models during treatment and report the patient state to the clinician.

3 Results

Patient recruitment and healthy volunteer data collection are underway. Cloud resources (SOSCIP, https://saans.ca) are online and under continuous development. Analysis of the available data and neural network performance against our clinician "gold standard" is ongoing.

4 Conclusion

We expect that development of these data-based, observational techniques will be an important tool in training new clinicians, and improving patient outcomes by rapidly and consistently identifying changes in patient SAANS signs and symptoms to clinicians. This information may enable early reporting of over or under treatment and offers additional opportunities for dynamically tailored patient-specific therapy.

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