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

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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 Rehab Centre.

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.

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.

Strategy and Features

At this point in the study the available data are limited: there are few patients and their time under treatment tends to be short. To make the most of this biometric data, we extract features reflecting typical biomechanical measures of stability (Centre of Pressure) using force plate data, heart rate variability and breathing rate from ECG, and approximate joint angles from 3D motion capture. These data form a time series which are used as inputs for machine learning. With more data available, it may be possible to perform machine learning directly on input data without extensive feature extraction.

The clinician observations, actively collected during patient treatment, are used to identify regions of elevated SAANS response. These regions are used in training a neural network to identify symptoms of elevated SAANS response in the biometric data.

With a trained predictor of SAANS response, biometric data can be processed in a computational pipeline and fed to the predictor to provide a delayed online predictor of SAANS response without clinician intervention.

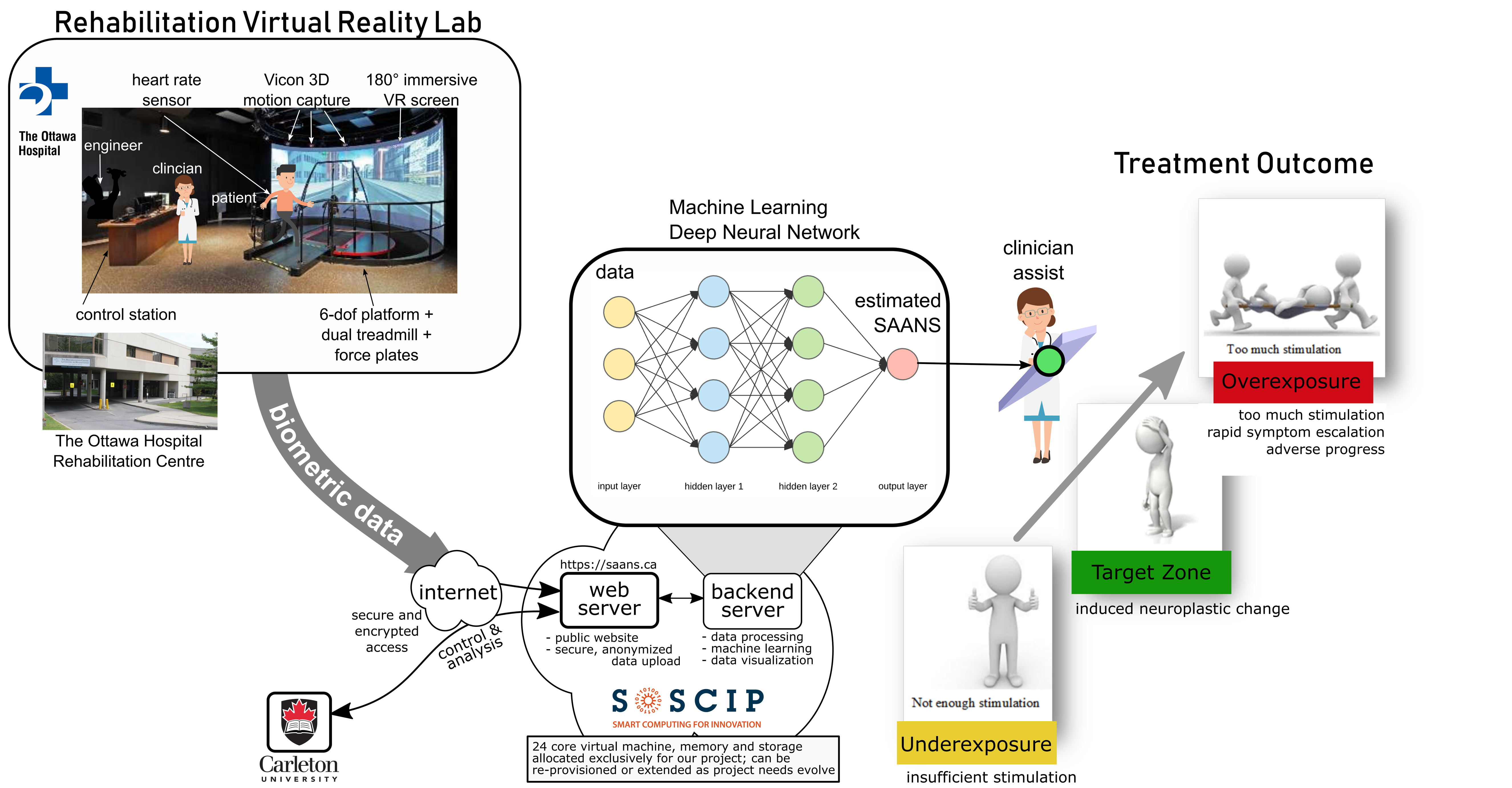

Figure 1: Biometric data collected during treatment is processed on cloud servers where machine learning is used to predict SAANS response. The predicted SAANS response can eventually be used to improve patient care by better targeting the ideal treatment zone. The predictor may also be used to support clinician training in detecting patient's SAANS response.

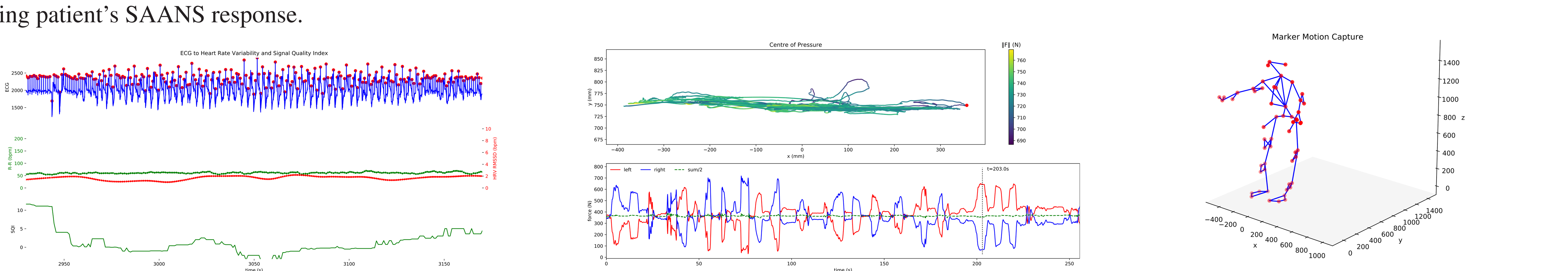

Figure 2: Processed biometric data: ECG to Heart Rate Variability, force plates to Centre of Pressure, and markers to "skeleton" motion.

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.

Quick Facts

Control Subjects	8	✓
Patients	5 of 60	
Study End Date	July 2020	
Stimulus	Clinician Treatment	
	CAREN VR	
Biometric Data	ECG, Force Plates	heart rate, breathing
	3D Motion Capture	movement, balance
Observations	Tablet	SSQ, signs & symptoms

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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Ethics Approval: This study was approved by the research ethics boards of both the Ottawa Hospital and Carleton University.

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