The Development of an Intelligent Haptic Upper-Limb Stroke Rehabilitation Device

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Introduction

Stroke is one of the major causes of disabilities in Canada [1]. Each year, approximately 40,000 to 50,000 strokes occur, of which 75% or more can improve quality of life through reaching task therapy [2].

Motivated by limited access to one-on-one stroke rehabilitation therapy, we are proposing to use robotic and artificial intelligence technologies to automate some of these exercises. Furthermore, with the aid of robotics and virtual reality augmentation, such a device may provide a new modality of therapy.

Objective

The goal of this proof-of-concept research is to determine if an intelligent haptic device can deliver reaching motion upper-limb therapy for moderate-level stroke clients.

The Exercise

The exercise we are focusing on is a forward reaching motion task with emphasis on the shoulder and elbow to rehabilitate client upper-limb proximal stability. Figure 1 provides a basic overview of the reaching exercise.

This exercise is important as it is the basic motion used for many activities such as grasping objects and other activities of daily living. Incorporating resistance into the exercise helps to improve coordination and strengthen muscle control, which will provide support and anchoring for other body movements (e.g. pushing down on a chair to stand up or using handrails on stairs for support).

(a) (b)

Fig. 1: Exercise for (a) forward and (b) outward reaching. Other variations of this exercise include up/down at an incline/decline.

The Interface

Robotic devices provide the physical interface between the system and user as well as supplying feedback and monitoring of the user during operation. In this new system, a haptic-enabled platform delivers resistance and directional guidance for the exercise. Three sets of sensors (triplex sensors) observe an array of information. A novel elbow extensor stimulation device assists the user when necessary.

Haptic Platform

This is the foundation for clients to perform the exercises. Figure 2 is the near final design. Features of the platform are:

- two degree-of-freedom haptic feedback
- adjustable for various reaching exercises
- swappable end-effector
- laterally independent
- unbounded client movement

Fig. 2: Haptic platform

Triplex Sensors

The sensor types used are encoders, photo-resistors, and interface querying. These will provide:

- comprehensive, yet non-intrusive, monitoring of client
- accurate hand movement mechanics
- monitoring of proper upper-limb posture
- physical and psychological fatigue level

Targeted Stimulation

Targeted stimulation to appropriate muscles will help the client associate muscle groups to movements. As represented in Figure 3, vibration cells will be used to stimulate the elbow extensor muscles.

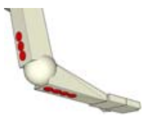

Fig. 3: Elbow stimulator

The Control System

The control system is responsible for guiding the client through the exercise. It must be able to autonomously adjust the exercise parameters (e.g. resistance, target distance) to the abilities of each client and increase the difficulty of the exercise as the client improves. The control system helps the client to reach their "goal" distance and resistance, while maintaining a controlled velocity back and forth. A partially observable Markov decision process (POMDP), an artificial intelligence method, was selected for this application.

POMDP

- An excellent model for sequential decision making
- Allows for uncertainty of state through observation probabilities
- Uses probability distribution over the current state space which depends on past observations (O), actions (A), and state space (S), and determines optimal course of action (Fig. 4 & 5)

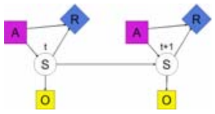

Fig. 4: General schematic of a POMDP model

- The POMDP agent obtains a reward/cost (R) after each action taken in the current state [3]

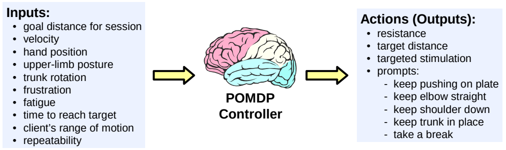

Fig. 5: Possible inputs and actions for the POMDP control system

Acknowledgements

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