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AN ADAPTIVE HOME-USE REHABILITATION SYSTEM FOR THE UPPER BODY

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INTRODUCTION

Musculoskeletal conditions are the most common causes of chronic disability in the world. The most common non-medication treatment for musculoskeletal disorders and stroke is rehabilitation. For patients, rehabilitation is a tedious chore that involves many months of treatment, resulting in low compliance. Rehabilitation regimens combine home-based exercises with therapist-monitored sessions; during the latter, the therapist assesses the patient's capabilities and adjusts the exercise tasks accordingly.

Previous research on upper body rehabilitation has shown that positive functional outcomes are achieved from programs that emphasize task-oriented, repetitive training exercises combined with biofeedback [5,7]. Thus, virtual reality (VR) rehabilitation systems have been developed that can repetitively simulate these task-oriented training exercises [3,6]. VR rehabilitation has been shown to be successful for improving upper body function in stroke patients, most likely because the interesting and engaging virtual tasks encourage increased repetition [6]. Furthermore, biofeedback has been shown to improve the learning rate during rehabilitation [5]. Finally, some VR rehabilitation programs have been designed to be used without the supervision of a physiotherapist [5].

However, VR rehabilitation must be able to adapt to the patients' changing capabilities. A previous study demonstrated that subjects trained with an adaptive VR rehabilitation system had improved upper body functionality when compared to subjects trained with conventional rehabilitation [4]. Unfortunately, these types of adaptive systems are cumbersome and expensive, and cannot be used outside of a medical or research facility.

The overall goal of this study was to create an adaptive home-use rehabilitation system. The specific goals were to collect data from the subject in real-time using simple and portable sensors, and then to create a customized exercise task for each subject by using the subject's previously collected data to adapt a standard exercise task.

METHODS

A. Description of the Rehabilitation System

A Microsoft Kinect™ sensor and an electromyograph (EMG) system were combined with custom software written in C++ in order to collect data from the subject in real time. Data was obtained from the Kinect™ using the official Microsoft software development kit (Kinect™ SDK, version 1.6, Microsoft, Redmond, WA, USA). The 3D joint position data (mediolateral, anteroposterior, and vertical axes) for 20 joints per subject were acquired at 30 Hz. Simultaneously, a wireless surface EMG system (Cometa, Milan, Italy) was used to collect electrical signals of the subject's biceps and triceps muscles at 1000 Hz. The linear envelopes of the EMG signals were processed in real-time using a previously described method (bandpass filter = 10 Hz - 500 Hz; lowpass filter = 30 Hz) [1]. The EMG data were normalized to the subject's maximum voluntary contraction (% MVC).

A 3D visual environment (VE) previously created using custom software in C++ and OpenGL [2] was modified to display the data from the sensors as well as the exercise task. The VE consisted of a virtual room (Figure 1, part A) where the joint center data of the subject was displayed as a skeleton figure. Separate from the VE, an additional window displayed the color video data from the Kinect™ as well as the real-time EMG data (Figure 1, part B).

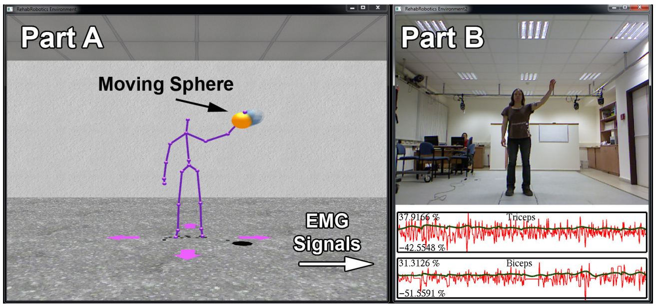

Figure 1: Visual environment: A) virtual room, B) color video and EMG data

B. Subject Testing

Eleven young, healthy subjects (age: 30.0 years ± 4.3, height: 169.7 cm ± 9.1, male = 5) with no history of upper body impairment volunteered to participate in this study. The subjects wore close-fitting short sleeve shirts to allow for the placement of two EMG electrodes, one on the biceps and one on the lateral head of the triceps. The exercise tasks for this study consisted of different types of visual follow tasks. For these tasks, a moving sphere was displayed in the VE (Figure 1) and the subject used his right hand to follow the sphere as closely as possible as it moved around the VE in a repeating cyclical 2D pattern for a total of 3 minutes. Biofeedback was used to aid the subject's accuracy; the sphere changed color and the volume of music playing in the background increased as the subject's hand approached the center of the sphere. In terms of data, the 3D position of the sphere, the 3D position of the subject's hand, and the subject's biceps and triceps EMG signals were recorded simultaneously during the exercise tasks.

The protocol for creating the customized exercise tasks, described previously by Barzilay and Wolf [2], consisted of generating a neural network that represented an inverse model of the subject. The subject was first asked to complete a training exercise task, which was either a vertical double figure 8 pattern [2] or a vertical half figure 8 pattern. The subject's performance during this training exercise (in terms of the 3D position of the hand, the 3D velocity of the hand, and the biceps and triceps EMG signals) was used as inputs to train the neural network; the 3D position and 3D velocity of the sphere were used as targets to train the neural network [2]. After the neural network was trained, it was used to simulate the subject's expected performance during a related exercise task, either a full horizontal figure 8 pattern or half of a horizontal double figure 8 pattern. Averaged EMG data from 10 healthy subjects were used as the additional inputs to the neural network [2]. The subject then completed both the exercise task output from the neural network (custom), as well as the unmodified original task used as input to the neural network (standard). Each subject completed 2 full sets for both types of training exercises. Every set consisting of a training task, a custom exercise, and a standard exercise (total of 12 exercise tasks per subject).

Analysis of the data was completed in MATLAB R2012a (Mathworks, Natick, MA, USA). For the custom and standard exercise tasks, the root-mean-square error (RMSE) was calculated between the subject's hand and the sphere for both position and velocity. For the EMG signals, the peak value and the area under the linear envelope were calculated. Finally, the data from the subjects were merged, and paired *t*-tests (two-tailed, $\alpha=0.05$) were conducted between the standard exercise data and the corresponding custom exercise data in the set for the aforementioned variables.

RESULTS AND DISCUSSION

The first specific goal for this research was to collect data from a subject in real-time using simple and portable sensors. During the subject testing, the Kinect^{TM} sensor measured the 3D position and 3D velocity of the subject's hand at 30Hz. Furthermore, the wireless surface EMG system measured the subject's biceps and triceps muscles and calculated the linear envelope of each signal at 1000Hz. Both these sensors are easily transportable and simple to use after minimal training. Thus, it is feasible to use the entire rehabilitation system in a home setting, as the only additional requirements are a computer and a display device like a television.

The second specific goal of the system was to create a customized exercise task for each subject. A neural network was created using the subject's training exercise data and was then used to modify a standard exercise task into a custom exercise task. A comparison of these two tasks (standard and custom) is presented in Table 1 below. There were no significant differences in the EMG variables. For both training exercises, the subjects had greater RMSE for the position and the velocity variables during the custom tasks (as compared to the standard tasks). In other words, during the custom task, their kinematic performance was worse in terms of accuracy to the instructed task.

These results show that the subjects were less able to replicate the custom task, suggesting that the custom task was more difficult to complete. This may be a result of the unconstrained nature of the neural network used to create the custom task. No output constraints were placed on the neural network, so the path of the custom task was somewhat squiggly and loopy; in contrast, the standard task was always a simple path. Consequently, the subjects were continually reacting to the unpredictable trajectory of the moving sphere during the custom task, but were able to anticipate the trajectory of the standard task, thereby making the standard task easier to complete. Adding constraints to the neural network could reduce the variability of the custom exercise.

CONCLUSIONS

This paper presented a feasible and functional adaptive home-use rehabilitation system for the upper body. The results indicate that the customized exercise tasks created by the system were more difficult to complete.

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Table 1: Averages and standard deviations for the kinematic and EMG variables by training exercise

			Kinematics		Biceps EMG		Triceps EMG	
Training Exercise	Output Exercise	Value	Position RMSE (cm)	Velocity RMSE (cm/sec)	Area (%MVC)	Peak (%MVC)	Area (%MVC)	Peak (%MVC)
Double Figure 8 Pattern	Standard	Average	5.71*	5.21**	762.01	25.99	849.04	25.40
		SD	1.1	0.8	488.4	18.6	516.1	17.4
	Custom	Average	6.18*	6.72**	759.91	25.93	846.75	25.41
		SD	1.0	1.2	485.0	18.7	513.3	17.5
Half Figure 8 Pattern	Standard	Average	5.87**	4.92**	779.81	24.43	847.93	28.65
		SD	1.2	0.8	512.9	17.0	577.8	25.6
	Custom	Average	6.39**	6.92**	778.33	24.41	844.40	28.73
		SD	1.3	0.9	511.1	17.0	596.0	25.6

Statistically significant differences by training exercise between standard and custom: $*p<0.05$, $**p<0.001$