Low-cost virtual reality system with passive arm support for stroke rehabilitation*

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***Abstract*— Stroke is a leading cause of long-term sensorimotor deficits in upper limb function. Yet, current upper limb interventions have limited effectiveness. Multiple efforts have been initiated for augmenting intervention with advanced technology, yet high system costs limit access to the technology. Planar movements constitute an important sub-set of motions that need to be re-trained following stroke. The current paper describes the development of a low-cost, virtual reality system with a supporting passive manipulator, suitable for training arm movement in the horizontal plane. To increase tracking accuracy, the system integrates two 3D cameras: a Kinect and a Leap Motion. A camera reference-frame calibration algorithm is presented.**

I. Introduction

Stroke is a leading cause of long-term sensorimotor disability with deficits in upper limb function persisting into the chronic stage in a large proportion of stoke survivors [1]. This is partly due to the limited effectiveness of current upper limb rehabilitation interventions [2]. Since repetition is a key element in post-stroke rehabilitation, multiple efforts have been initiated for augmenting rehabilitation following stroke with advanced technologies, such as robotics and virtual reality (VR) [3-4], which can support and motivate more intensive motion repetition. VR enables the creation of enriched practice environments leading to increased motivation and improved practice, relevant to activities of daily living. Robots facilitate limb support and control of motion dynamics. Additionally, these technologies can be used to monitor the patient's motion and thus can provide objective progress assessment.

High-intensity, repetitive training is an essential component to facilitate motor recovery which may however, be limited by the high cost of adopting rehabilitation technologies such as VR and robotic systems. Making VR and robotic-based training affordable is challenging since precision and robustness of low-cost systems is typically low, which limits their utility. If a VR system represents motion imprecisely, the participant may learn non-optimal motion profiles with unwanted characteristics. This may contribute to the phenomenon of 'learned dis-use' and lead to the learning of maladaptive movement patterns [5]. In the current research, we set out to develop a low-cost, yet accurate and robust VR training system with an anti-gravity support passive manipulator for whole-arm upper limb stroke rehabilitation.

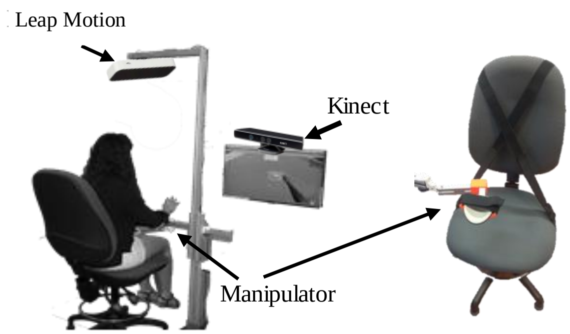

Figure 1. Developed system. Left: complete system, Right: chair and supporting manipulator.

II. System

A. System overview

The developed low-cost system supports planar, horizontal whole-arm motion. Such movement is frequently encountered in activities of daily living and many existing high-cost upper limb rehabilitation robotic systems, e.g., the MIT-Manus (now In-Motion) [6] have been constructed for such movement. While upper limb movement in 3D space is important, constructing an arm support mechanism for such movement is complex. In comparison, supporting planar horizontal movement is less challenging, more affordable and therefore suitable for the current effort.

The system comprises three modules. A passive manipulator for supporting horizontal motion against gravity, motion tracking with Kinect and Leap Motion cameras, and an interactive VR game environment to enhance motivation. The participant sits in a chair with a high backrest and no armrests. When needed, trunk motion is limited by two crossed Velcro straps attached to the chair's backrest, to reduce compensatory trunk motion. The system limits endpoint motion to the horizontal plane. Whole arm motion is recorded and used as input to the game environment presented on the screen.

B. The supporting manipulator

The supporting passive manipulator was modeled after an ergonomic computer desk armrest. Such devices support the arm while facilitating smooth horizontal motion. The manipulator has two links and three horizontal joints. The wrist is placed on a padded wrist holder and connected to the

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manipulator using a Velcro strap. The hand is free, so the participant can use it for making task relevant motion.

An effort was made to support comfortable motion throughout the arm workspace, while keeping the manipulator simple and small. Three link-size configurations were tested (Table 1). With the original armrest and the first prototype, motion range was limited, and task execution was uncomfortable. The second prototype facilitated smooth motion throughout the workspace while still having a small footprint. In this system, the manipulator is connected at an adjustable vertical level to a supporting stand that is connected to a large weight (about 50kg) for stability. The stand is also used for placing the cameras.

TABLE I. MANIPULATOR LINK LENGTHS

Version	*Link 1 [mm]*	*Link 2 [mm]*
Original arm-rest	122	111
First prototype	170	150
Second prototype	170	185

C. *Motion tracking*

Arm motion is tracked using low-cost 3D cameras. Preliminary tests were conducted for assessing whether the accuracy of the Kinect camera alone was sufficient. Three different camera locations and six wrist locations in the horizontal plane were tested in four participants. The average error of estimating the elbow extension angle was 10°, which is high. We aim at reducing the error to about 1°.

Due to the low accuracy of the single Kinect camera, we decided to perform tracking based on fusion of two 3D cameras. The Kinect camera has a larger field of view yet lower accuracy then the Leap Motion camera. Therefore, they were combined to attain high accuracy for gross arm motion. The Kinect camera is placed facing the participant about 150cm away and the Leap Motion camera is connected to the stand about 40cm above the participant's wrist. Attaching the camera from the side was also considered but since 3D camera precision in the parallel plane is typically greater than its depth precision, the location above the hand was preferred.

A rigid transformation between the respective reference frames of the Kinect and Leap Motion cameras is required for integrating their outputs. The Leap Motion camera returns only 3D locations of a limited set of landmarks, such as fingertips, palm, wrist, and elbow positions. Such landmarks can be used for aligning reference frames. Prior work [7] calibrated the Kinect and Leap Motion cameras based on fingertip locations and the Corresponding Point Set Registration (CPSR) algorithm [8]. As fingertip locations are not readily available from the Kinect SDK, their locations were extracted from the Kinect 3D image.

In the current system, camera position is set during system setup, and both cameras are statically connected to their base placement. Therefore, we developed a two-stage calibration procedure, which utilizes these constraints. An initial transformation matrix is measured based on camera position and orientation. In the second stage, the matrix is optimized based on landmark positions recorded in parallel from both cameras. Since the SDK's of both cameras identify wrist and elbow locations, these are used as landmarks. Data are recorded as the participant moves his arm throughout the workspace. The participant's movement profile is semi-static, i.e., the participant moves slowly and holds a posture for a few seconds and then moves again. To reduce recording noise, movement samples in the static positions are averaged. The static position coordinates of both cameras serve as inputs to an optimization algorithm. The constrained-optimization function in the Matlab™ optimization toolbox[1] is used, where the initial transformation matrix is the matrix computed during the initial stage. A non-linear equality constraint is imposed so rotation matrix orthogonality is maintained,

$$R^{-1} = R^{T} \tag{1}$$

The calibration procedure was tested by recording 3000 elbow position samples from both Kinect and Leap Motion cameras. Thirty static elbow positions were identified and 10 samples were averaged for each static position, for each camera. With the optimized transformation matrix, the average difference between transformed Kinect readings and Leap Motion readings across all static positions was 4.7 cm, which is acceptable taking into account inaccuracies in determining elbow joint center of rotation.

D. *The interactive game environment*

A sample game was programed using the Unity™ game development engine. The programed game is of a simple task of feeding a fish. A fish bowl and fish food appear in different positions on a virtual table. The participant must take the food and bring it to the fish. The food is taken and released based on the proximity of the hand to the target location, i.e., based on gross arm motion. When food is successfully released, a star appears on the screen. Participants have a time-period within which they should complete the task. The duration of this period can be adjusted based on the participant's capabilities. The participant's success score (number of times food reached the fish within the time-period) is presented on the screen. There are three different target positions for the fish bowl and three food positions, making nine fish-food combinations. These combinations are repeated during each training session, where the number of repetitions is adjusted according to the period allotted for performing the task and the determined training duration. The camera view selected in the

Figure 2. Game environemnt. One fish bowl-food position combinations presented.

[1] https://www.mathworks.com/products/optimization.html

game is a first-person view, so that the view of the game arena and the arm movement are unobstructed (Fig. 2).

III. Conclusion

The basic components of a low-cost VR rehabilitation system with anti-gravity support for horizontal upper limb motion have been developed. We are currently developing a model integrating camera measurements with environment and biomechanical constraints, e.g., arm segment length and horizontal wrist motion plane, for improving joint angle computations. We are also enhancing the game environments, calibrating the food and fish bowl positions to the participant's arm length so that the objects are perceived as reachable. Additionally we are testing addition of negative feedback when the trunk is used for reaching a target within arm's length.

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