

Evaluation Approach for Post-stroke Rehabilitation Via Virtual Reality Aided Motor Training

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Abstract. This paper introduces an evaluation approach that was applied to clinical data collected from a virtual reality aided motor training program for post-stroke rehabilitation. The goal of the proposed evaluation approach is to diagnose the patient's current status (performance) and detect change in status over time (progression). Three measures, *performance time*, *movement efficiency*, and *movement speed*, were defined to represent kinematic features of reaching. 3-D performance maps and progression maps were generated based on each kinematic measure to visualize a single patient's behavior. The case study revealed the patient's current status as to direction and range of upper extremity reach ability, composed of pitch, yaw and arm length. Further, progression was found and visualized quantitatively over a series of practice sessions.

Keywords: Virtual reality, rehabilitation, evaluation approach, human computer interaction.

1 Introduction

1.1 Background

In the US, more than 700,000 people annually suffer a stroke, an event that is a leading cause of long-term disability [1]. This disability can manifest itself as difficulty in performing activities of daily living such as dressing, preparing and eating a meal, bathing, or work related tasks. As such, quality of life may be severely impacted by stroke [2][3] and more effective methods for rehabilitating lost functioning are a high priority. Fortunately, loss of upper extremity (UE) function can be improved via task-oriented motor training which promotes practice of relevant movements, is highly repetitive, and increases in intensity based on patient progress. A good motor training task should be designed to target a specific functional deficit (i.e., pointing, grasping, reaching) and the intensity of exercise should be based on both ongoing status and desired therapeutic goals such as increased movement speed,

accuracy, efficiency, and range.. However, motor-training tasks used in conventional therapy are limited in their capacity to systematically control stimulus presentation and precisely capture motor performance in real time. Problems with the controlled manipulation of physical exercise objects limit the ability to vary intensity level in a flexible and dynamic way. Moreover, data collected during conventional therapy process is often too limited in type and extent to reliably evaluate the status or performance of the patient. Finally, one possible factor in the mixed outcomes found in rehabilitation research may be in part due to the inability to maintain a patient's motivation and engagement when presenting him with a repetitive series of training challenges. Hence, the integration of gaming features in virtual reality (VR)-based rehabilitation systems to enhance client motivation is viewed as an important direction to explore. Patient motivation may be minimal when there is little immediate meaningful real time feedback from the physical environment after a long exercise session.

A VR interactive system provides numerous assets for rehabilitation beyond what is currently available with traditional methods [4][5]. One of the cardinal benefits of this form of advanced simulation technology involves the capacity for systematic delivery and control of stimuli. In this regard, an ideal match exists between the stimulus delivery assets of VR simulation approaches and rehabilitation requirements for progressive and variable practice. This "Ultimate Skinner Box" asset can provide value across the spectrum of rehabilitation approaches, from analysis and training at an analog level targeting component cognitive and physical processes (i.e., selective attention, grip strength, etc.) to the complex orchestration of more complex integrated functional behaviors (e.g., planning, initiating and physically performing the steps required to prepare a meal in a distracting setting). This asset can also be seen to allow for the hierarchical delivery of stimulus challenges across a range of difficulty levels. In this way an individual's rehabilitation can be customized to begin at a stimulus challenge level most attainable and comfortable for him, with gradual progression to higher functional difficulty levels based on the individual's performance. Another strength of VR for rehabilitation is that it allows the creation of simulated realistic environments within which performance can be tested and trained in a systematic fashion. By designing virtual environments that not only "look like" the real world, but actually incorporate challenges that require real world functional behaviors, the ecological validity of rehabilitation methods could be enhanced. As well, within a virtual environment (VE), the experimental control required for rigorous scientific analysis and replication can still be maintained within simulated contexts that embody the complex challenges found in naturalistic settings. Thus VR derived results may have predictive validity and clinical relevance for the challenges that clients face in the real world. Further, with the use of advanced sensing systems in VR, a large quantity and wide variety of high quality data can be captured to assist in the rehabilitation process. Finally, VR-oriented tasks can be equipped with game features that provide real-time visual, auditory and haptic feedback not only to motivate the patient but also to make the patient feel present within the virtual world. Thus far, early research suggests that the use of VR technology is valuable in improving motor skills for post-stroke rehabilitation of functional deficits including reaching [6], hand function [7] and walking [8] [9].

1.2 Previous Work

We developed a virtual reality aided motor training task, static reaching, for post-stroke rehabilitation of functional upper extremity (UE) reaching. The interactive system was designed to allow individualized practice based on level of ability and allow therapist driven progression to achieve therapeutic goals. Within the VE, the patient reaches to multiple targets with synchronized arm and hand movements of the paretic side as shown in Fig. 1. The work space for each patient was defined in relation to individual shoulder position and arm length. Targets were specified in 3-D space by defining pitch, yaw, and percentage of arm-length as shown in Fig. 2. A more detailed description of this task has been reported previously (Stewart et al, Luke – did you previously report the system?).

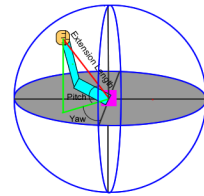
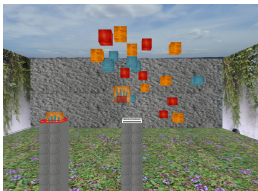


Fig. 1. Virtual reality aided motor training task: static reaching

Fig. 2. Determination of target location

A clinical test using this VR task (along with 3 others) was conducted with five patients post-stroke. Volunteers were screened to see if they meet the inclusion criteria: 1) stroke at least one month prior to the pilot trial; 2) over the age of 18 years; 3) able to attend 12 training sessions at the Motor Behavior and Neurorehabilitation Laboratory at the University of Southern California. Subjects are excluded if they had a Mini-Mental Status Exam score below 24, significant limitations in passive range of motion, or no active movement in the hemiparetic UE. Five subjects passed the screening and participated in the trial. According to their initial UE Fugl-Meyer motor scores, the severity of their motor impairment was classified as severe or moderate as shown in Table 1.

Table 1. Severity of disability of subjects

ID	101	102	103	105	106
Severity	Severe	Severe	Moderate	Moderate	Moderate

1.3 Overview

One of the challenges in applying such a system to stroke rehabilitation is developing a method to detect and quantify a patient’s status and progress over time using the collected motion data. In this paper, we first define three kinematic measures to indicate movement performance. Then, we represent each measure with a 2-D pitch-yaw grid map that indicates performance based on target location within the

workspace. Next, we integrate the kinematic measures with the pitch-yaw map to generate a 3-D performance map that allows visualization of the patient's current status and development of methodologies to evaluate progress over sessions. A case study is presented with the data collected from one subject post-stroke who practiced this VR task for 12 sessions over 3 weeks.

2 Evaluation Approach

2.1 Kinematic Measures

Three types of kinematic measures, performance time, movement efficiency and movement speed, were used to quantify reaching performance. All measures were derived from the continuous position and orientation data of an electromagnetic tracker placed on the hand at a data acquisition rate ranging from 60Hz to 80 Hz.

Performance time (PT) was defined as the period between the time when the virtual hand left the start position and the time the virtual hand collided with a target in 3-D space. It provides an index of movement time without regard to the length of the movement path. A lower value indicates faster trial performance. Movement efficiency (ME) was defined as the ratio of the actual movement path over the shortest possible movement path, the linear distance between the start position and the position of the virtual target. ME is an index of how efficiently the patient achieves the target. A lower value of ME indicates better reach efficiency.

Movement speed (MS) was defined as the ratio of the actual movement path over performance time.

2.2 2-D Pitch-Yaw Grid Map

We developed a method to represent workspace location defined by pitch, yaw and arm length with a series of 2-D pitch maps as below in Fig. 3. For each arm length ratio (from 10% to 120%), the zone for each combination of pitch and yaw angle was projected onto a plane diagram. Each grid on the 2-D map represents a certain location in the reaching workspace. Also, each grid indicates a certain 3-D position in space.

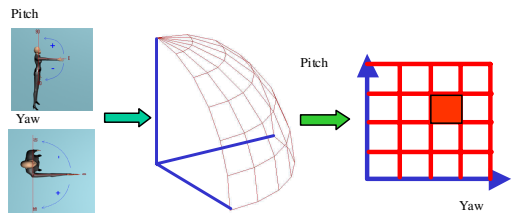


Fig. 3. Translation of target location at a given arm length to workspace location and projected onto a 2-D pitch yaw grid map

2.3 Average Chart and Slope Chart

Average chart and slope charts were built via a two-step classifying process. Data for all test trials were grouped into multiple datasets where each dataset included the data belonging to a specific grid on the pitch yaw map. Each dataset was further classified

into multiple sub-datasets according to session number of completion. Kinematic measures were derived for each sub-dataset. Then, for each kinematic measure, an average value and slope value of multiple sub-datasets belonging to each dataset were calculated. Average and slope values were placed into separate charts that specified grid location. The same procedure was repeated for each grid location on both the average and slope charts. This procedure is summarized in Fig. 4.

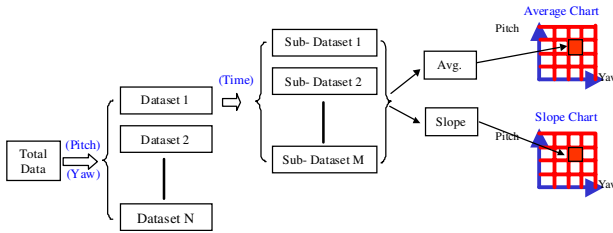


Fig. 4. Development of average chart and slope chart

2.4 Performance Map

A 3-D performance map was built by extracting the value from each grid of the average chart as shown in Fig. 5. Current status could then be visualized and compared from grid to grid via the 3-D performance map. For PT and ME, the lower the height of the bar, the better the performance. For MS, the higher the height of the bar, the better the performance.

2.5 Progression Map

A 3-D progression map was built by extracting the value from each grid of the slope chart as shown in Fig. 6. A positive slope represents a positive trend on progression for MS (improving performance) but represents a negative trend on progression for PT and ME (decreasing performance). In order to simply analysis and comparison, the sign of the slope was reversed for PT and ME so that a positive slope equated to a positive progression trend for all three measures. All negative slopes were then reset to zero and classified as showing no progression based on the assumption that a subject’s performance could not become worse over practice. Further, change of status was visualized and compared from grid to grid via a 3-D progression map.

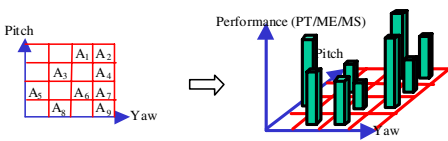


Fig. 5. Creation of the 3-D performance map

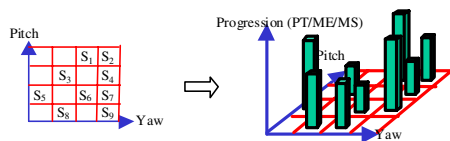


Fig. 6. 3D progression map

2.6 Level Classification

Both performance and progression were classified into three levels and labeled in different colors on the 3-D map. Thus, the user can quickly perceive and locate current status or change of status.

Performance was classified as “Excellent”, “Good” or “Fair”. All performance data was sorted by its value from better to worse. The mean of the first half of each data set was established as the cutting point between “Excellent” and “Good”. Then, the mean of the second half of each data set was established as the cutting point between “Good” and “Fair”.

Progression was classified as “Significant”, “Minor” or “None”. After all signs were made positive as mentioned above, negative data sets were labeled as “None” indicating no progress. The mean of the remaining data was established as the cutting point between “Significant” and “Minor”.

3 Case Study

Due to the large amount of data collected for the 5 patients, subject 103 was selected for case presentation and to demonstrate the described evaluative approach.

3.1 Visualization of Performance: Arm Length Ratio 60%

For each kinematic measure (ME, MS or PT), the performance chart was built using all extracted data sets. The cut-off values used to classify the status levels for this subject are shown in Table 2. The 3-D performance map is shown in Fig. 7 and labeled with different colors to indicate the level of current status: red stands for “Excellent”, blue stands for “Good” and green stands for “Fair”.

At an arm length ratio of 60%, the results show that the subject’s best PT fell within the zone defined by pitch from 15 to 60 degrees and yaw from -40 to 60 degrees. Poorer performance in PT appears mostly with pitch values higher than 60 degrees. With respect to ME, the subject performed better when pitch was lower than 75 degrees and yaw lower than 60 degrees. With respect to MS, the subject moved at slower speed when pitch was higher than 90 degrees or lower than 15 degrees.

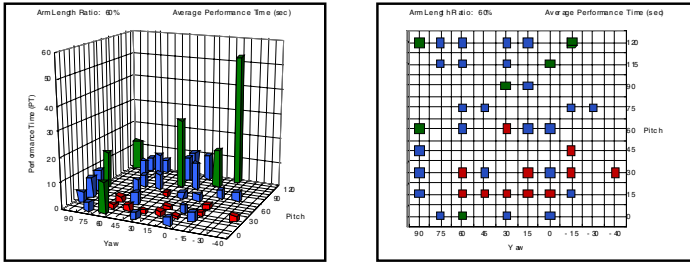
Table 2. Performance level classification

<i>Performance</i>	PT (sec)	ME	MS
Excellent	$PT < 2.49$	$ME < 1.41$	$MS < 33.42$
Good	$2.49 < PT < 10.77$	$1.41 < ME < 3.24$	$19.27 < MS < 33.42$
Fair	$PT > 10.77$	$ME > 3.24$	$MS > 19.27$

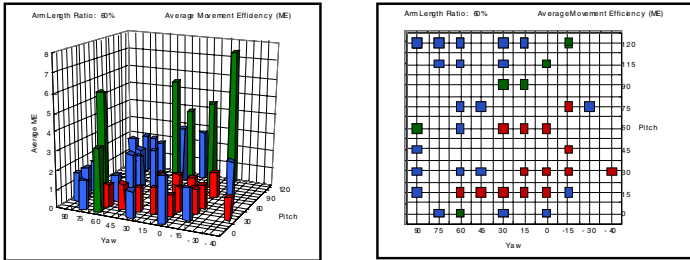
Table 3. Progression level classification

<i>Progression</i>	$-S_{PT}$	$-S_{ME}$	S_{MS}
Significant	$-S_{PT} > 2.46$	$-S_{ME} > 0.56$	$S_{MS} > 5.36$
Minor	$0 < -S_{PT} < 2.46$	$0 < -S_{ME} < 0.56$	$0 < S_{MS} < 5.36$
None	$-S_{PT} < 0$	$-S_{ME} < 0$	$S_{MS} < 0$

(a) PT



(b) ME



(c) MS

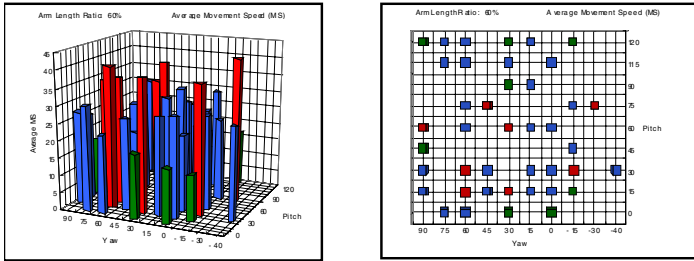


Fig. 7. Performance map of each kinematic measure

3.2 Visualization of Progression: Arm Length Ratio 60%

A progression chart was built for each performance measure. The cut-off values for each level of progression for this subject are shown in Table 3. Also, a 3-D progression map for each kinematic measure is shown in Fig. 8, with different colors indicating the level of progression, where red stands for “Significant”, blue stands for “Minor” and green stands for “None”.

“Significant” progression for PT was found primarily at pitch values of 120 degrees while no progression was found predominantly in the zone defined by pitch values below 90 degrees and yaw values below 45 degrees. “Significant” progression on ME occurred in a zone with either pitch higher than 90 degrees or yaw higher than 45 degrees. For MS, significant progress was only seen in a zone with yaw values higher than 60 degrees.

3.3 Overview of Performance Versus Arm Length Ratio

The mean of each kinematic measure for all zones was calculated for each arm length ratio. (Fig. 9) It indicates that PT increased gradually with increased arm length ratio. However, ME showed no significant change until the arm length ratio reached 100%. At arm length ratios greater than 100%, ME increased rapidly.

3.4 Overview of Progression Versus Arm Length Ratio

At each arm length ratio, the percentage of zones that fell within each progression level was calculated. (Fig. 10) At an arm length ratio equal to or higher than 85%, the percentage of zones in progression on PT and ME is obviously higher than for other arm length ratios. However, MS has the highest percentage of zones in progression at two extremes of the arm length ratio: 25% and 120%.

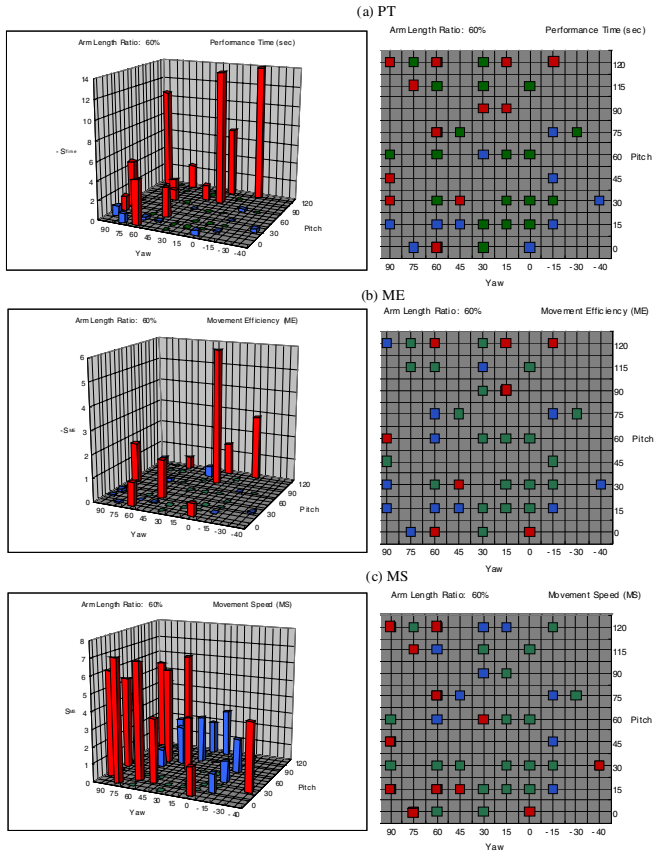


Fig. 8. Progression map of kinematic measures

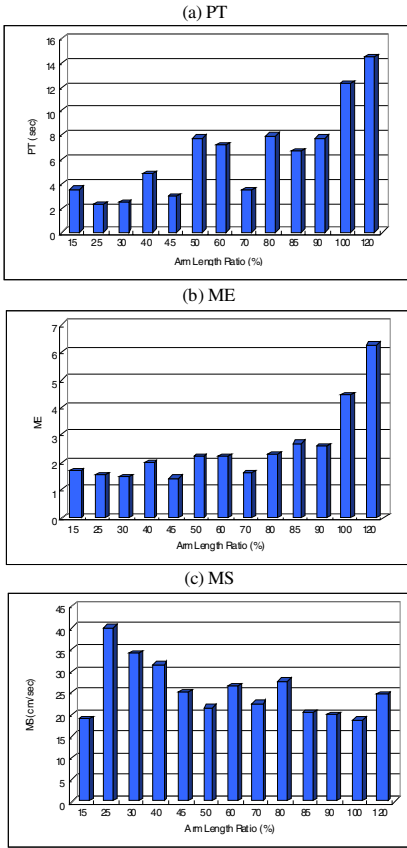


Fig. 9. Performance versus arm length

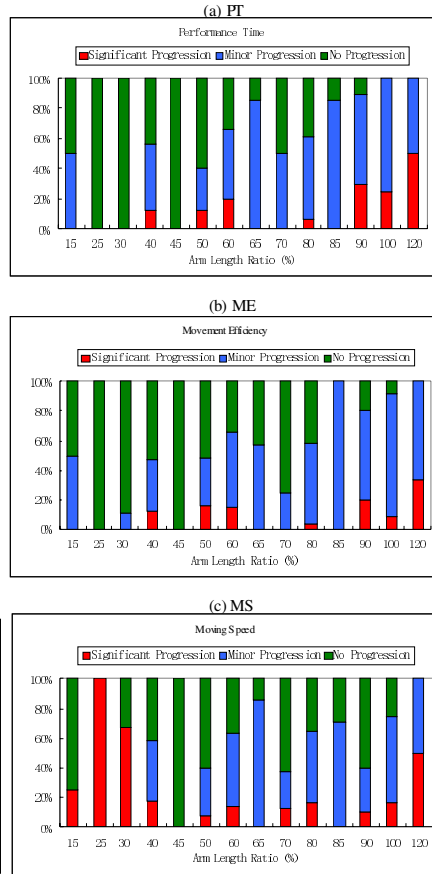


Fig. 10. Performance versus arm length

4 Conclusion and Future Work

4.1 Conclusion

A VR aided upper extremity motor training system was designed to meet the needs of both patients and therapists. Representative measures, PT, ME and MS were defined to represent kinematic features of performance. An evaluation approach was developed to generate performance and progression maps that allowed visualization of the current status (performance) and the change in status over sessions (progression) of kinematics measures.

The presented case study of subject 103 reveals the patient’s current status with respect to his/her range of reach ability composed of pitch, yaw and arm length. Further, progression of movement ability was found and visualized over a series of practice sessions for this individual. Progression occurred predominantly in zones with lower initial performance levels.

4.2 Future Work

Analysis of the remaining subjects' data will be completed to further investigate the statistical model. A larger scale clinical trial including both patients' post-stroke and healthy controls is needed to provide a more robust data set for further study. Advanced learning-based algorithms will be developed to allow systematic analysis of large amounts of data across multiple dimensions of movement. Further, an easy-to-use tool for evaluation of a patient's current status and progress over sessions needs to be developed to assist the clinician in decision making and treatment planning.

Acknowledgments. This research was supported in part by National Institutes of Health Roadmap Initiative grant # P20 RR20700-01 and by the Integrated Media Systems Center, a National Science Foundation Engineering Research Center, Cooperative Agreement # EEC-9529152, with additional support from the Annenberg School for Communication, University of Southern California.

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