Correlation of Reaching and Grasping Kinematics and Clinical Measures of Upper Extremity Function in Persons with Stroke Related Hemiplegia*

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***Abstract*—Timed measures of standardized functional tasks are commonly used to measure treatment effects in persons with upper extremity (UE) paresis due to stroke. The effectiveness of their ability to measure motor recovery has come into question because of their inability to distinguish between motor recovery and compensations. This paper presents three linear regression models generated from twelve kinematic measures collected during the performance of a two phase reach/grasp and transport /release activity as performed by 21 persons with upper extremity hemiparesis due to chronic stroke. One of these models demonstrated a statistically significant correlation with the subjects' scores on the Wolf Motor Function Test (WMFT), a battery of fifteen standardized upper extremity functional activities. The second and third models demonstrated a statistically significant correlation with the subjects' WMFT change scores elicited by a two week intensive upper extremity motor rehabilitation intervention. The high correlation suggests that models of kinematic measurements can be used to predict neurologic improvement and the effectiveness of treatment.**

I. Introduction

Paresis of the upper extremities is one of the major problems post stroke. Although many approaches have been used for recovery of upper extremity function, the critical part of post stroke rehabilitation, measurement of the effectiveness of these interventions, still needs some improvement. Timed measures of standardized functional tasks have become popular because of their high levels of ecological validity; however, the effectiveness of their ability to measure motor function has come into question because of the inability of timed measures to distinguish between true motor recovery and effective but abnormal compensatory movement patterns[1].

Changes in kinematic measures have been utilized in the rehabilitation literature to document changes in the ability of persons with stroke to move their upper extremities through space [2]. The complexity of the interaction between the UE of persons with neurologic recovery and real world objects limit the ability of any single lab-based kinematic measure to describe these changes effectively. Several authors have examined models of multiple kinematic measurements and their correlations with standardized clinical tests of UE function [3, 4] as well as change in these measures due to intervention [4] and the ability of these models to predict change in clinical measures due to intervention [4, 5] .

In this paper we examined the correlation between kinematic measures of upper extremity function and the Wolf Motor Function Test (WMFT), a clinical test with a battery of 15 timed standardized functional movements of the upper extremity. High correlation between models of these kinematic measures and the WMFT will help establish the face validity of these models for the detection of change in UE motor function and also help establish the ecological validity of these measures for the quantification of change in the ability to interact with real world objects. We will also examine optimized models of UE kinematics in an attempt to identify key measurements for the description of UE function, the measurement of change in UE function and prediction of the ability to make changes in UE function due to an intervention.

II. Methods

A. Subjects

Subjects were a group of twenty six persons mean (±SD) age 51(±11) who have had their stroke at least 9 months prior to testing and training (mean (±SD) = 70.4 (±50) months. Subjects demonstrated UE impairment due to ischemic stroke (n=22) or hemorrhagic stroke (n=4). Mean Chedoke McMaster Impairment Inventory Arm Stage was 5.3 (±1). Mean Chedoke McMaster Impairment Inventory Hand Stage was 4.6 (±1). Mean composite of Ashworth Scale scores for shoulder extensors, elbow and finger flexors was 3.2 (±2).

B. Training System and schedule

Fifteen subjects participated in robot and VR assisted training and eleven subjects in clinical rehabilitation consisting of repetitive task practice (RTP) for two weeks. For robot/VR training New Jersey Institute of Technology Robot Assisted Virtual Rehabilitation (NJIT-RAVR) system and NJIT TrackGlove system were used. These systems improve subjects' upper extremity motor function by requiring three dimensional movements of the shoulder, elbow, wrist and fingers of patients during training [6].

C. Data collection

Reach to grasp task was performed by subject pre and post training. Subjects were asked to put their hand at the consistent preset initial position. Then they were asked to reach to object when cued then grasp the object to targeted position and release (see Fig. 1). Four objects were designed

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so that they have different size and shapes: small circle (diameter d=3.2cm), small cube (l=9.5cm, w=3.2), big circle (d=5.7cm), big cube (l=6.7cm, w=5.7cm). During the experiment, subjects wore an instrumented glove (CyberGlove®) with twenty two sensors to obtain finger joint angle measurements in real time. It was synchronized with a trackSTAR system that acquired wrist, elbow, shoulder and sternum positions at the frequency of 100Hz. Custom scripts written in Matlab and C++ were utilized for data acquisition. Prior to data collection, Cyber Glove sensors were calibrated with three hand postures, flattened hand with fingers together, hand in a closed fist, flattened hand with fingers stretched apart corresponding to zero degrees and ninety degrees in finger flexion, and twenty degrees in finger abduction, respectively.

Clinical Measurements Wolf Motor Function Test (WMFT) measurements, a timed evaluation of upper extremity performance that measures limb and joint movement [7] , were taken pre and post training. Basically the higher the WMFT indicate more impairment.

D. Primary Data analysis

Twelve kinematic measurements of a reaching,-grasping-and-transporting-release movement were calculated to show changes between pre- and post-training test (Table1).

E. Secondary Data Analysis

Least squares multiple linear regression was used to examine the correlation between kinematic and clinical measures. The first step was to find a linear regression model that can estimate WMFT from all twelve kinematic measurements. Since kinematic data were normally distributed, z-normalization was conducted prior to the analysis. The second step was to eliminate kinematic measurements dependency upon each other with stepwise linear regression analysis and to identify major contributors (kinematics measurements). Coefficient of determination R^2 was calculated in order to evaluate model performance.

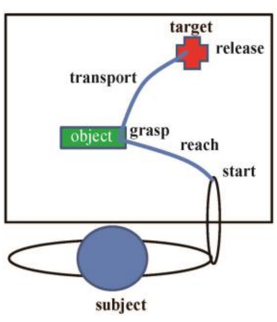

Figure 1 . Reaching test schematic: Trial begins with hand at rest, placed in initial preset position. At cue, subject reaches for the object, places it on a 7.5 cm high target platform, and returns to initial position.

TABLE I. Kinematic Measures

Measurements, abbreviations	**Description (units)**
Reaching Phase	
Hand Trajectory Length, **RHTL**	Length of path the hand travels during reaching (cm)
Hand Trajectory Smoothness, **RHTS**	Normalized integrated jerk calculated during reaching
Hand Peak Velocity, **RHPV**	Measured during reaching (mm/sec)
Time to Peak Velocity, **RTPV**	Time to achieve peak velocity during reaching (sec)
Elbow/Trunk Excursion Ratio, **RETR**	Difference in elbow joint angle at completion of reaching and Elbow joint angle at onset of reaching (deg) / difference in trunk position at completion of reaching and trunk position at onset of reaching (cm).
Maximum Finger Extension, **RMFE**	Index finger angle at maximum extension during reaching (deg).
Finger Excursion, **RFE**	Change in index finger angle from beginning of reaching to maximum finger extension (deg)
Transport Phase	
Hand Trajectory Length, **TTL**	Length of path the hand travels during the transport phase (from the point when object was grasped until object is released at the target) (cm)
Hand Trajectory Smoothness, **TTS**	Normalized integrated jerk calculated during the transport phase
Hand Peak Velocity, **TPV**	Measured during Transport (mm/sec)
Time to Peak Velocity, **TTPV**	Time to peak velocity during the transport phase (sec)
Elbow/Trunk Excursion Ratio, **TETR**	Difference in elbow joint angle at offset and onset of transport (deg) / difference in trunk position at offset and onset of transport (cm).

Abbreviations of measurements for the reach-and-grasp portion of the movement start with letter R, and for the transport-release portion of the movement with letter T.

III. RESULTS

A. Predicting clinical scores from kinematic measurements (Model 1).

The following model (Eq. (1)) uses pre-test kinematic measurement scores to predict pretest WMFT scores and post-test kinematic scores to predict post-test WMFT scores. High correlation between WMFT scores predicted by this

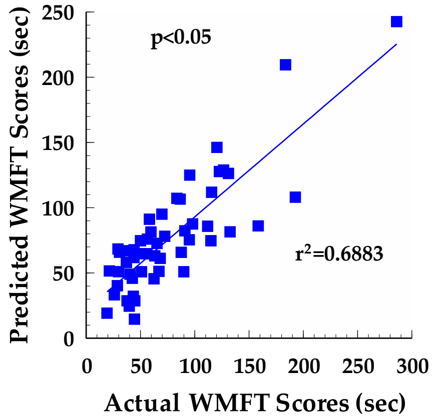

Figure 2. Model # 1 WMFT Scores predicted with a model using all twelve kinematic measurements, major contributors were: RETR and TTTL. Higher numbers indicate slower times / worse performance.

model and actual WMFT scores (R^2= 0.7119, $p<0.05$) is observed (See Figure 2).

WMFT = 77.1084 + 5.56197 **[RMFE]** - 6.24909**[RFE]** + 9.20259 **[RHTL]** + 15.3964 **[RHTS]** + 20.1293**[RETR]** +13.8166**[TTL]** + 2.40292**[TTS]** - 2.06312 **[TETR]** + 8.00461**[RHPV]** + 1.84725 **[RHPV]** + 1.22779 **[TPV]** + 8.53163 **[TTPV]** (1)

Following stepwise regression, an enhanced model predicting WMFT scores from kinematic measures is presented in Eq.2. Correlation between WMFT scores predicted by this model is moderate (R^2=0.6883, $p<0.05$). In this model **RETR** and **TTL** are the major contributors.

WMFT = 77.1084 - 6.13741 [**RFE**] + 7.66842[**RHTL**] +15.9652[**RHTS**] + 17.6837 [**RETR**] + 18.0784 [**TTL**] - 1.49122 [**TETR**] (2)

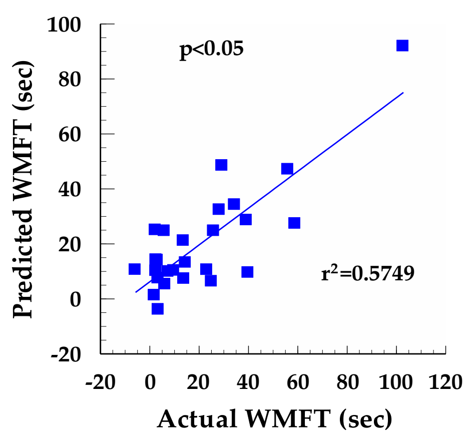

Figure 3. Model # 2 WMFT Change Scores predicted with a model using **change** scores for all twelve kinematic measurements, (major contributors were: RHTS and TTL) vs. actual WMFT **change** scores. Positive numbers correspond with functional improvement.

B. Predicting therapy-induced changes in WMFT scores from changes in kinematic measurements (Model 2).

The following model (Eq.3) uses changes in kinematic measurement scores after training to predict changes in WMFT scores after training. Correlation between WMFT scores predicted by this model is moderate (R^2=0.6692, $p<0.05$) (See Figure 3).

WMFT-Change (post-pre) = - 20.7483 + 2.25536 **[*RMFE*]** +7.71844 **[*RFE*]** + 5.30849**[*RHTL*]** + 2.50859 **[*RHTS*]** + 1.5463**[*RETR*]** - 17.9099 **[*TTL*]** - 5.27136 **[*TTS*]** + 4.62443 **[*TETR*]** - 1.09701 **[*RHPV*]** - 1.43264 **[*RTPV*]** - 4.28617 **[*TPV*]** +15.6417 **[*TTPV*]** (3)

Following stepwise regression, an enhanced model predicting WMFT scores from kinematic measures is presented in Eq.4. Correlation between WMFT scores predicted by this model is moderate (R^2=0.5749, $p<0.05$). Considering standardized predictors, RHTS and TTL provided the largest contribution to the model.

WMFT-Change (postminpre) = -20.7483 + 1.5265 **[RFE]**+ 2.44744 **[RHTL]** + 12.6192**[RHTS]** + 0.737369 **[RETR]** - 18.4042**[TTL]** + 0.786927**[TETR]** (4)

C. Predicting therapy-induced changes in WMFT scores with pre-training kinematic measurements (Model 3).

The following model (Eq.5) uses change scores for all kinematic measurement scores to predict change scores on the WMFT. Correlation between WMFT scores predicted by this model is high (R^2=0.7797, $p<0.05$).

WMFT = -20.7483 + 2.11104 **[RMFE]** + 7.93709 **[RFE]** + 14.3117 **[RHTL]** - 3.75847 **[RHTS]** - 1.45387 **[RETR]** - 18.9314 **[TTL]** + 4.14153 **[TTS]** - 8.87039**[TETR]** - 4.11828 **[RHPV]** - 2.20693**[RHPV]** + 2.04246 **[TPV]** + 0.410069**[TTPV]** (5)

Following step wise regression, an enhanced model predicting changes in WMFT scores from initial kinematic measures is presented in Eq.6. Correlation between WMFT scores predicted by this model is high (R^2=0.7414, $p<0.05$) (See Figure 4) .RHTL, TTS and RFE provided largest contribution to the model.

WMFT = -20.7483 + 8.19867 [**RFE**] + 10.8782 [**RHTL**] - 3.34775 [**RHTS**] - 2.51885 [**RETR**] - 14.5958[**TTS**] - 7.79483 [**TETR**] (6)

IV. DISCUSSION

The statistically significant correlation between scores on the WMFT, a battery of timed functional tasks, and a model of kinematic measures consistent with improvements in motor control suggests that WMFT score and tests like it may at least in part describe real changes in motor control contrary to the opinions of authors describing these measures as indicators of effective compensatory strategies. The optimized version of Model 1 contains measurements of the

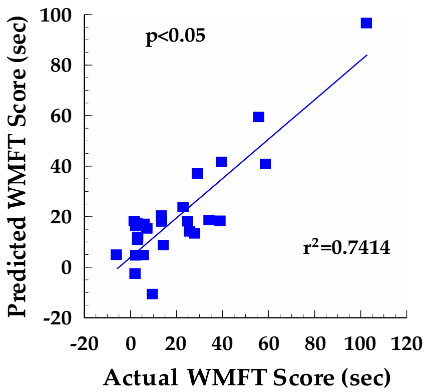

Figure 4. Model # 3 WMFT Change Scores predicted with a model using all twelve kinematic measurements **collected at initial measurement** (major contributors were: RTS, TTS and RFE) vs. actual WMFT **change** scores. Positive numbers correspond with functional improvement.

ability to extend the fingers and perform an accurate, efficient reaching movement using smaller amounts of trunk movement as compared to elbow movement. All are aspects of normalized motor control without compensatory strategy.

The statistically significant correlation between the models of change in kinematics and WMFT change score support this assertion as well. The optimized version of Model 2 contained a measure of trajectory smoothness. Changes in this measurement have been cited as an indicator of neurologic recovery in persons with stroke. This kinematic measurement was also a significant contributor to models of two measures related to motor recovery, the Upper Extremity Fugl Meyer Assessment and the Motor Status Score in a previously published study by Bosecker[3]. Correlation between kinematic measures of real world object interaction and clinical measures in this study were similar to the correlation between robotically created kinematics and clinical measures in our previous study [4]. This model also contained measures of the ratio of elbow movement to trunk displacement for both of the two hand transport movements considered. Impairments in this ability are considered one of the hallmark features of upper extremity hemiplegia[8]. Improvements in these two movements explaining the variance in improvements in WMFT scores further support the notion that changes in the WMFT may indicate neurologic improvement in persons with stroke.

A baseline level of motor recovery is generally considered a pre-requisite for an improvement in UE function due to an intervention. Interestingly, the optimized version of Model 3 contained RFE, maximum finger excursion during reaching, a measurement of the ability to open the hand as well as RHTS, a measurement of hand trajectory smoothness during reaching. Both of these abilities are considered indicators of neurologic recovery in persons with CVA. The coefficients for these two measures were positive indicating that higher scores on these parameters were consistent with larger improvements in WMFT. Two other major contributors to this optimized models included the length of the trajectory required to perform a standardized reaching movement and the amount of elbow extension in proportion to trunk movement. In this sample longer, more inefficient reaching trajectories and small amounts of elbow movement as compared to abnormally high levels of trunk movement were associated with larger improvements following intervention. This may suggest that these impairments are amenable to behavioral intervention. Also, these measures may be useful as clinical screening tools for identifying patients with the prerequisite motor function to benefit from motor interventions. In addition, a majority of the measurements that made substantial contributions to the predictive ability of all three of the models were collected during the transport phase of the movement This phase requires patients to extend the elbow as they abduct and flex the shoulder against gravity. This action is challenging for persons with UE paresis and may prove to be an indicator of motor function improvement.

V. Conclusion

We developed three linear regression models using kinematic measurements collected during reaching, grasping and object transport performed by persons with UE hemiparesis secondary to stroke. The predictions of these models demonstrated statistically significant correlations with WMFT scores as performed by the same subjects and with the change in WMFT score after a two-week long intensive UE motor training program.

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