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Correlations between Statistical Models of Robotically Collected Kinematics and Clinical Measures of Upper Extremity Function*

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Abstract

One of the obstacles in the development of rehabilitation robotics has been inadequacy in the measurement of treatment effects due to interventions. A measurement tool that will efficiently produce a large reliable sample of measurements collected during a single session that can also produce a rich set of data which reflects a subject's ability to perform meaningful functional activities has not been developed. This paper presents three linear regression models generated from seven kinematic measures collected during the performance of virtually simulated rehabilitation activities that were integrated with haptic robots by 19 persons with upper extremity hemiparesis due to chronic stroke. One of these models demonstrated a statistically significant correlation with the subjects' scores on the Jebsen Test of Hand Function (JTHF), a battery of six standardized upper extremity functional activities. The second and third models demonstrated a statistically significant correlation with the subjects' change scores on the JTHF.

I. Introduction

Robotics have been examined as a possible modality for the remediation of upper extremity (UE) impairments caused by stroke for over two decades. One of the obstacles in the development of these technologies has been the inadequacies in the measurement of treatment effects due to interventions[1]. UE function is a varied and complex set of behaviors with a multitude of factors affecting the ability to use an impaired UE in the real world. Clinical measurements of function typically produce fairly volatile results with patients performing extremely well during the performance of a single repetition of an activity and then poorly on the next[2]. In addition, these clinical tests typically produce a

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single piece of information describing a single aspect of movement, necessitating a wide variety of tests to be performed to produce a data set that will reflect the whole of UE ability. Developing a measurement tool that will efficiently produce a larger more reliable sample of measurements collected during a single measurement session, that can also produce a rich set of data may be necessary to produce a useful picture of a patient's motor function.

Utilizing robots to collect kinematics during simulated UE activity may fulfill these requirements. The robots can collect data as patients perform large number of repetitions of these activities in a short time. Robots can also collect meaningful measurements of the various roles of the UE in a single repetition, decreasing the number of movements that are needed for testing.

The largest obstacle in the utility of these measurements is the need to establish that measurements of an UE interacting with a robot will reflect the ability to interact with real world objects [3]. This paper will attempt to establish the development of mathematical models of a set of kinematic measurement of shoulder, elbow and finger movement, collected during three hour sessions interacting with the New Jersey Institute of Technology Robot-Assisted Virtual Rehabilitation (NJIT RAVR) system performing integrated UE tasks. These models will be developed and tested three ways, first, for their correlation with scores on the JTHF measured on the same day by the same subjects, second, for a model of pre to post test changes of these measures to correlate with changes in JTHF score subsequent to an eight session intervention using the NJIT RAVR System and third, we will examine the correlation of a model of pretest kinematic measurements scores with pre to post test change scores on the JTHF Test of Hand function, subsequent to an eight session intervention using the NJIT RAVR system.

II. Methods

A. Subjects

Subjects were a group of 19 persons mean age 56 (±13) at least 9 months post stroke (mean=70 months ± 66). Eighteen had ischemic strokes, one a hemorrhagic stroke, that resulted in mild to moderate UE impairment. Mean Chedoke McMaster Impairment Inventory Arm Stage was 5(±1). Mean Chedoke McMaster Impairment Inventory Arm Stage was 4 (±1)[4]. Mean composite of Ashworth Scale scores for shoulder extensors, elbow and finger flexors was 4 (±1).

B. Training System & Schedule

Subjects trained using the NJIT RAVR system, which is a combination of a Haptic Master ™, (Moog, The Netherlands), a three degrees of freedom robot (position of the wrist in three dimensional space accomplished by movement of the elbow and shoulder), a ring gimbal (Moog, The Netherlands) which adds an additional 3 degrees of freedom (forearm: yaw, pitch and roll) and a CyberGlove™ (Ascension, USA). This combination measures arm and finger positions in three dimensional space that are interfaced with a suite of complex virtual simulations used to retrain integrated movements of the arm and hand in persons with strokes. The second training system is the NJIT Trackglove system, a combination of a CyberGlove™ (Ascension, USA) and a trackStar 3-dimensional magnetic tracking system, which is used to measure hand and finger movements integrated with virtual environments in a similar fashion to that of the NJIT RAVR system. These systems are described in detail elsewhere [5, 6]. The training period was 8 days, 2–3 hours with subjects performing four simulations that train the hand, arm and fingers as an integrated functional unit each day. The protocol is described in detail elsewhere [7].

C. Data Collection

Robotically collected kinematics Subjects performed training using four simulations but kinematics measurements were collected during two simulations, the Hammer Task simulation and the Virtual Piano Trainer simulation, because these two simulations utilize discrete movements that are well suited for kinematic measurements. Kinematic measures described in this study were collected during the first day of training and the last day of training.

Clinical test of UE function for this study was the JTHF, a battery of six standardized functional activities, involving the manipulation and transport of small objects [10]. The six items are timed and summed, making smaller numbers indicative of better performance. This data was collected one day prior to training and one day after the completion of training.

D. Primary Data Analysis

Robotically collected kinematics for the hammer task include *hand-path length*, a linear measurement of total path the hand goes in order to reach the target. Overall time to complete the Hammer simulation task in seconds is reported as *hammer duration*. *Trajectory smoothness*, a measurement of the ability to produce smooth, coordinated, gross reaching movements, is analyzed using normalized integrated jerk(NIJ).NIJ was calculated as follows:

$$NIJ=\sqrt{\frac{T^5}{2L^2}\int_o^T J^2 dt} \quad (1)$$

where T= duration(s), L = Length of trajectory(cm), J is jerk, the third derivative of hand displacement. Lower NIJ score indicates smoother hand trajectory.

Finally, we evaluated *end point deviation (EPD)*, a measure of proximal stability and shoulder stabilization during hand-object interaction[8].This variable is measured in centimeters and calculated:

$$\mathrm{EPD}=(\mathrm{E}_1+\mathrm{E}_2+\mathrm{E}_3\ldots\ldots\ldots\ldots+\mathrm{E}_{\mathrm{final}}) \quad (2)$$

where E_1= one second average of distance between endpoint and target center after target has been acquired, and E_{final}= 1 second average of distance between endpoint and target center immediately preceding target completion. Lower EPD score indicates more stability of the arm during hand-object interaction. These kinematic measurements are discussed in greater detail in [5] and [9].

Virtual piano kinematics include *key press accuracy*, the total number of correct keys pressed during virtual piano trainer simulation performance during a training day divided by the total number of keys pressed. *Piano duration* is the average time to complete a key press starting when a note is cued and ending when the correct key is pressed. *Fractionation score* (FS) describes the ability to flex a finger independently of other fingers. FS is calculated as follows:

$$\mathrm{FS}{=}\beta \mathrm{active} - \beta \mathrm{nonactiv} \quad (3)$$

Where β_{active} is the angle of the active finger's metacarpophalangeal (MCP) joint and $\beta_{nonactive}$ is the MCP angle of the most flexed inactive finger. These kinematic measurements are discussed in greater detail in [6].

E. Secondary Data Analysis

In order to evaluate the correlation between kinematics and clinical measurements to test each of the three hypotheses, two different regression analysis approaches were used. Since the points in residual plots were randomly dispersed around the horizontal axis we decided to find a linear regression model that can estimate JTHF. In the first approach, we calculated the model to estimate from all robot kinematics. Certain aspects of the kinematic measurements are dependent upon each other. In an effort to eliminate co-linearity we conducted a principal component analysis (PCA) followed by a stepwise regression to eliminate kinematic metrics whenever possible. There were seven measurements each with different units, we normalized the data so that the mean is 0 and standard deviation is 1 for each measurement, prior to PCA process. Following this step, least squares error multiple linear regression models were constructed. Finally, performance for each of the three models was measured by the correlation between the predicted JTHF score and the actual JTHF score using a Pearson Correlation coefficient.

III. Results

A. Predicting single scores

The model utilizing pre-test kinematic measurement scores to predict pretest JTHF scores and post test kinematic scores to predict post-test JTHF scores was:

$$\begin{aligned}\mathrm{JTHF}{=}&101.8044+(13.3469)\\ &\times[\mathit{key\ press\ accuracy}])\\ &-(1.0484\times[\mathit{piano\ duration}])\\ &-(31.1721\times[\mathit{FS}]\\ &+(53.2945\times[\mathit{hand\text{-}\ path\ length}])\\ &-(29.1174\times[\mathit{hammer\ duration}])\\ &+(12.2301\times[\mathit{smoothness}])\\ &+(17.9140\times[\mathit{EPD}]).\end{aligned} \quad (4)$$

Correlation between JTHF scores predicted by this model and actual JTHF scores was moderate (R^2=0.5702, p=1.06e-04).

Following step wise regression, an enhanced model predicting JTHF scores from kinematic measures was as follows:

$$\begin{aligned}\mathrm{JTHF}=&95.8746+(11.1763\times[\mathit{key\ press\ accuracy}])\\&-(31.7069\times[FS])+(36.2125\times[\mathit{hand\text{-}\ path\ length}])\\&+(15.2958\times[EPD]).\end{aligned}\quad(5)$$

Correlation between JTHF scores predicted by this model was moderate (R^2=0.5579, p=3.4206e-06).

B. Predicting change in JTHF scores with change in kinematic measurements

The model utilizing change scores for the seven kinematic measurement scores to predict change scores on the changes scores on the JTHF

$$\begin{aligned}\mathrm{JTHF}=&12.0449+(24.9018\times[\mathrm{key\ \ press\ \ accuracy}])\\&+(15.8544\times[\mathrm{piano\ \ duration}])\\&+(28.5961\times[\mathrm{FS}])\\&-(25.9248\times[\mathrm{hand{-}path\ \ length}])\\&+(34.5042\times[\mathrm{hammer\ \ duration}])\\&-(0.5341\times[\mathrm{smoothness}])\\&-(22.1432\times[\mathrm{EPD}]).\end{aligned}\quad(6)$$

Correlation between JTHF scores predicted by this model and actual JTHF scores was moderate to high (R^2= 0.7371, p=0.009).

Following step wise regression, an enhanced model predicting JTHF scores from kinematic measures was as follows:

$$\mathrm{JTHF}=47.5178+(7.3581[\mathit{key\ press\ accuracy}])+(\mathit{32.3683}[FS])-(\mathit{4.4018}[\mathit{hand\text{-}\ path\ length}])-(13.9073[EPD]).\quad(7)$$

Correlation between JTHF scores predicted by this model and actual JTHF scores was moderate (R^2=0.5404, p=0.0105).

C. Predicting change in JTHF scores with initial kinematic measurements

The model utilizing change scores for the seven kinematic measurement scores to predict change scores on the changes scores on the JTHF:

$$\begin{aligned}\text{JTHF}= & -59.1830+(11.9672\times[key\ press\ accuracy])\\ & +(14.4097\times[piano\ duration])\\ & +(7.2316\times[FS])\\ & -(34.8526\times[hand\text{-}\ path\ length])\\ & +(50.7833\times[hammer\ duration])\\ & -(20.7707\times[smoothness])\\ & -(17.9889\times[EPD]).\end{aligned} \quad (8)$$

Correlation between JTHF scores predicted by this model and actual JTHF scores was moderate (R^2=0.6423, p=0.0417).

Following step wise regression, an enhanced model predicting JTHF scores from kinematic measures was as follows:

$$\begin{aligned}\text{JTHF}= & -20.2434+(11.9967\times[key\ press\ accuracy])\\ & -(64.0764\times[hand\text{-}\ path\ length])+66.7717\times[hammer\ duration]\\ & -(22.4390\times[EPD]).\end{aligned} \quad (9)$$

Correlation between JTHF scores predicted by this model and actual JTHF scores was moderate (R^2=0.5587, p=0.008).

IV. Discussion

Use of mathematical modeling of robotically collected kinematics has been attempted previously by Bosecker et al [3]. This group utilized a set of kinematics measured during a set of planar reaching tasks performed with the MIT-MANUS system to predict scores on the UE Fugyl-Meyer Assessment, Modified Ashworth Scale, Motor Status Score and Motor Power Scale. This study was the first successful attempt to compare the ability of an array of kinematic measurements collected during the interaction of patients with stroke and a robot to their ability to move in the real world. Several statistically significant correlations between the models produced and these impairment level measures were identified.

The process described in this paper extends this work by evaluating the ability of a model of robotic kinematics to describe the ability of persons with stroke to produce more complex, functional movements involving both object manipulation and transport. The ability of the NJIT RAVR and TrackGlove systems to collect kinematic data related to both proximal and distal movements may be critical to this ability as suggested by the retention of both proximal UE kinematic data as collected by the NJIT RAVR system and distal UE kinematic data as collected by the TrackGlove system in all three of the regression enhanced models.

The ability to measure proximal stabilization of the shoulder and elbow during object interaction may be of relative importance as well. All three regression enhanced models retained this metric which is unique to the NJIT RAVR system secondary to its ability to measure proximal kinematics during distal UE effector activity.

The statistically significant correlation between JTHF scores predicted by model utilizing change scores in robotic kinematics and actual changes in JTHF scores, suggests that improvements in in robotically collected kinematics may relate to changes in the ability to move independent of the robot. This could form the beginning of an argument supporting the use of robotic kinematics as an outcome measurement for trials of robotic rehabilitation independent of cross validation with clinical scores. Sensitivity to change due to an intervention is an important step in the validation of a measure of movement for use as an outcome measure in rehabilitation trials.

The statistically significant correlation between JTHF scores predicted by model utilizing pretest scores in robotic kinematics to predict and actual changes in JTHF scores may be the most important of the three discussed in this abstract. Rehabilitation interventions are expensive and time intensive for patients. Screening a potential patient for the ability to make functional improvements subsequent to a 24 hour robotic intervention as is described in this paper with approximately one hour of data collection would be an important step toward making robotic rehabilitation more cost efficient.

Several further studies will be necessary to evaluate our models conclusively. A larger sample of subjects with a broader range of impairments will need to be tested and validation of the predictive ability of models utilizing kinematic measurements of subjects not included in the development of the models will be necessary.

V. Conclusion

We developed three linear regression models using kinematic measurements during training sessions utilizing two different systems of virtually simulated activities interfaced with haptic robots performed by persons with UE hemiparesis secondary to stroke. These models demonstrated statistically significant correlations with single scores and change scores on the JTHF as performed by the same subjects.

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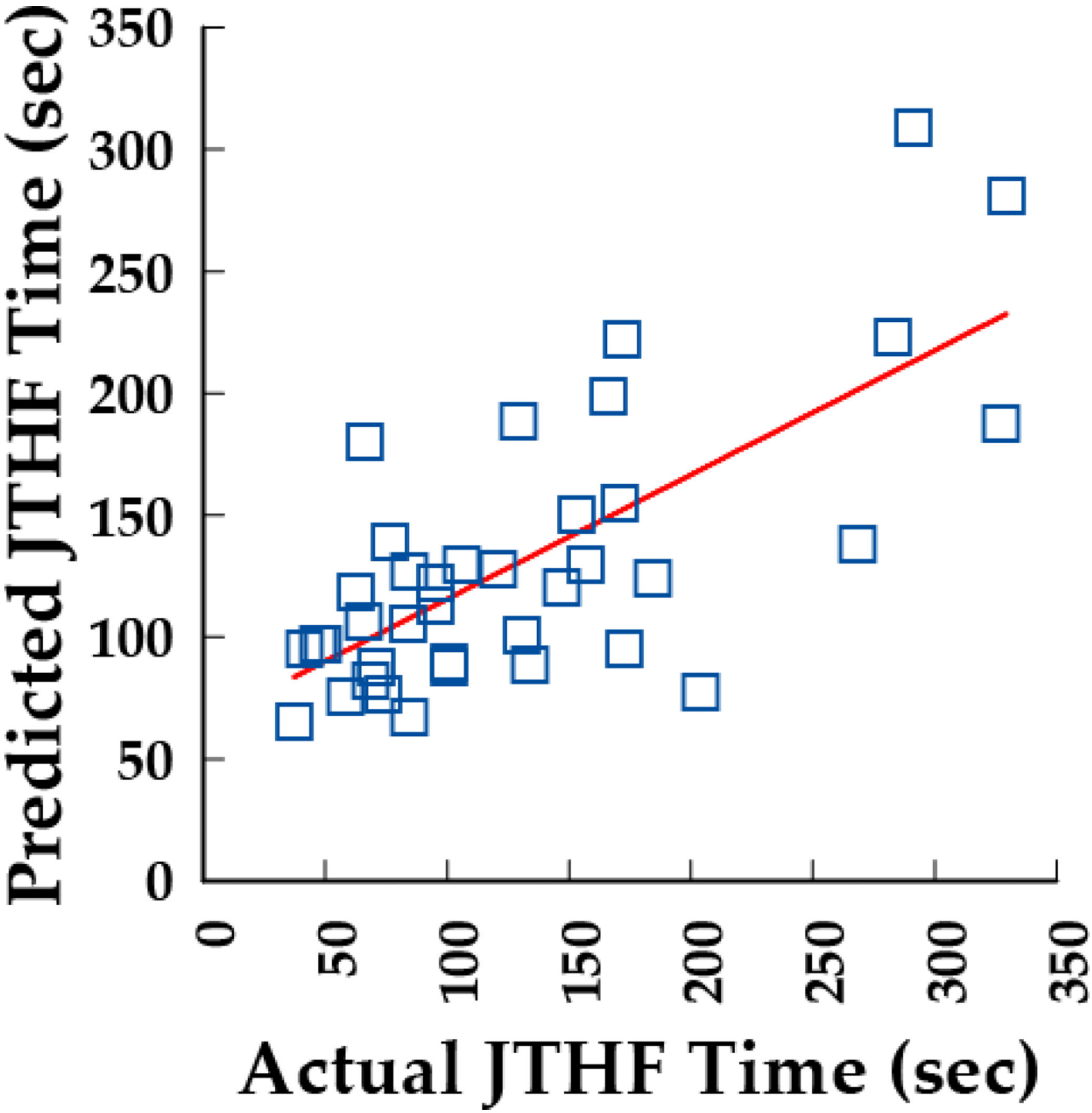

Figure 1.
Scatter plot of actual scores on JTHF in seconds on x-axis and model-predicted JTHF score on y-axis. Each subject is represented by two points, one for pre-test data and a second for post-test data. Lower values indicate better score.

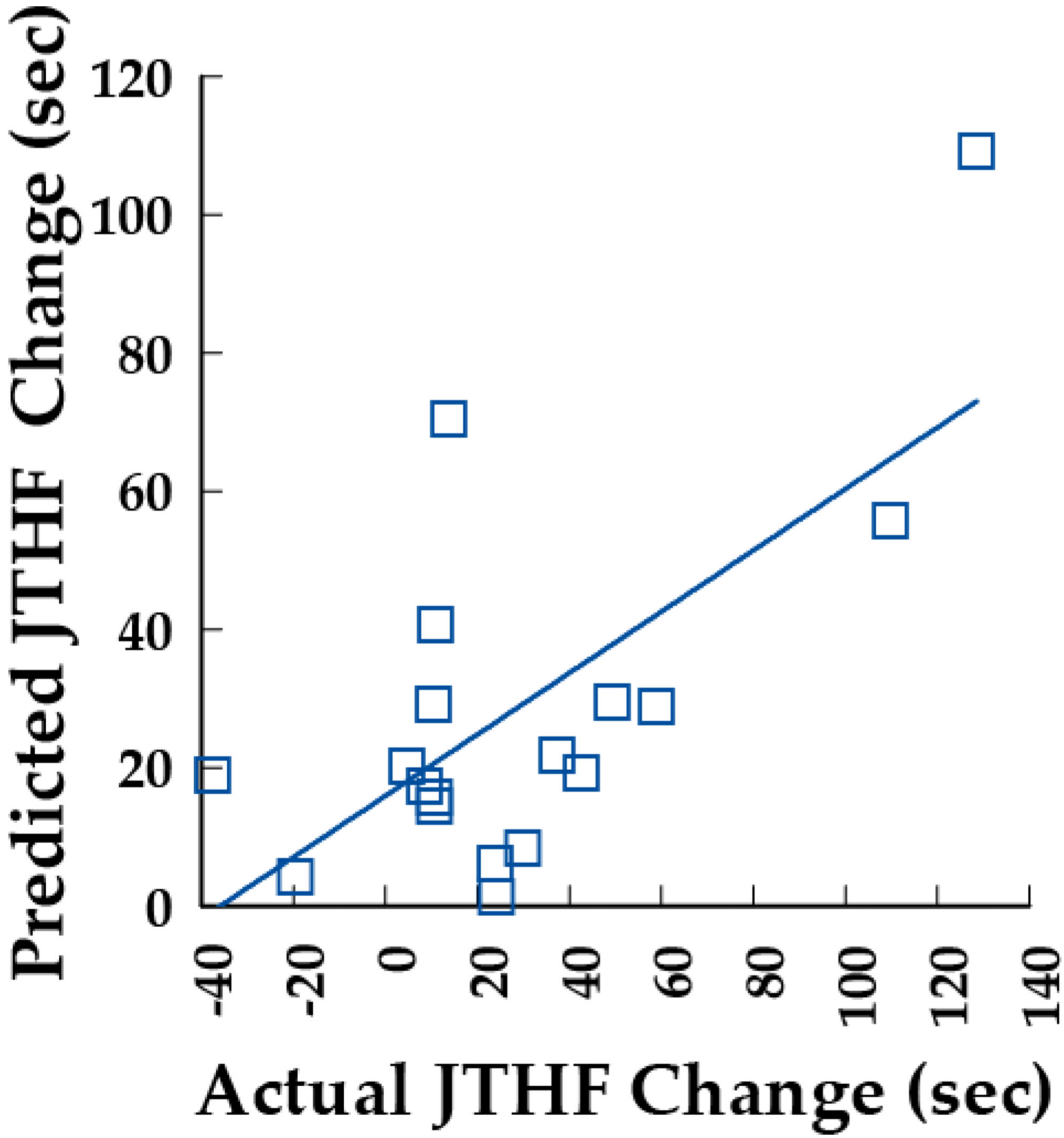

Figure 2.

Scatter plot of change scores for JTHF in seconds (pre test score minus post test score) on x-axis and model predicted scores on y axis. Model was generated from change in kinematics (pre test scores minus post test scores) and actual JTHF scores

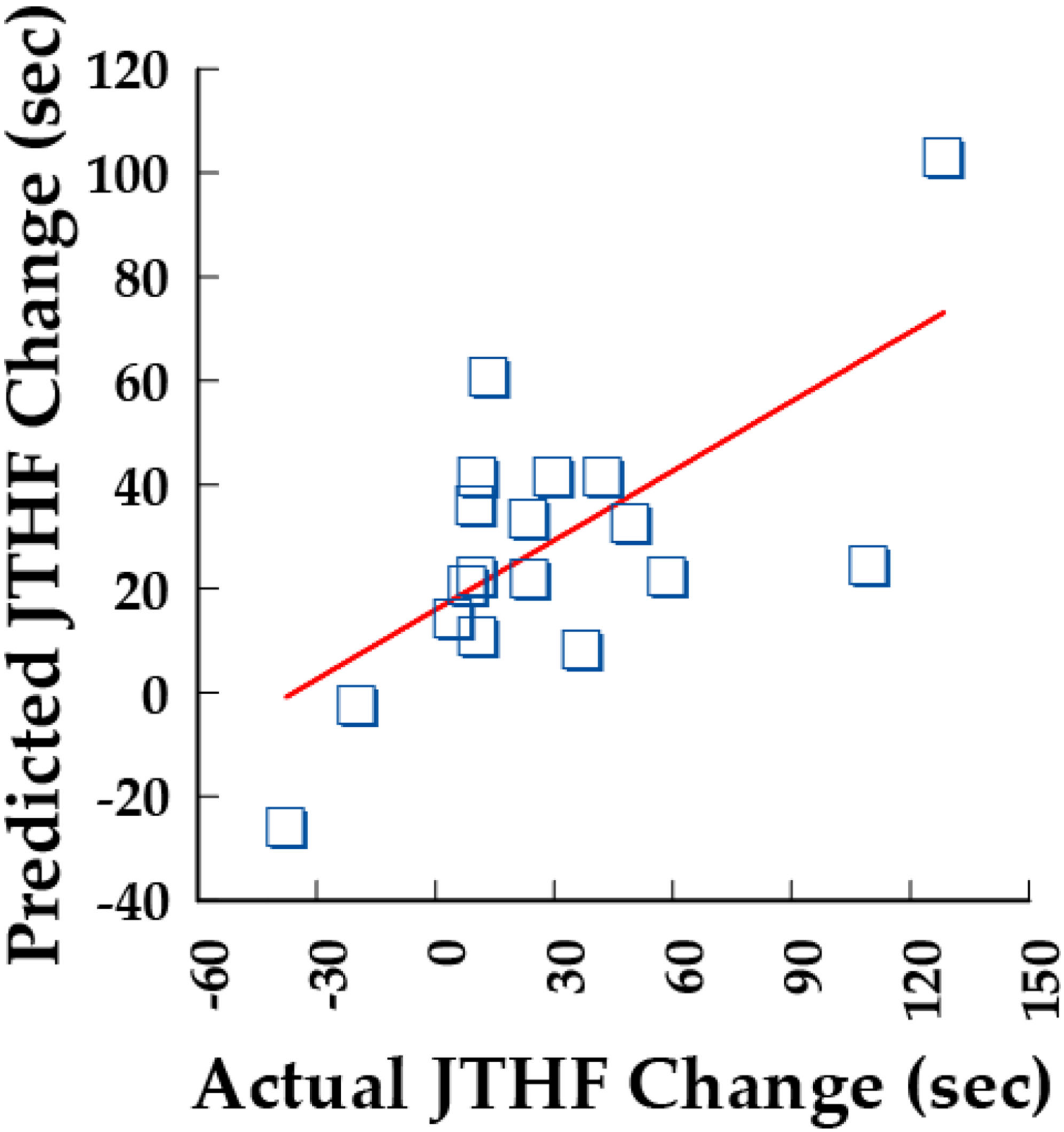

Figure 3.
Scatter plot of change scores for JTHF in seconds (pre test score minus post test score) on x-axis and model predicte scores on y-axis. Model was generated from pre test kinematics scores.