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Multivariate Nonlinear Regression Analysis of Trajectory Tracking Performance Using Force Reflecting Joystick in Chronic Stroke-induced Hemiparesis

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Abstract— **Individualizing a neurorehabilitation training protocol requires understanding the performance of subjects with various capabilities under different task settings. We use multivariate regression to evaluate the performance of subjects with stroke-induced hemiparesis in trajectory tracking tasks using a force-reflecting joystick. A nonlinear effect was consistently shown in both dimensions of force field strength and impairment level for selected kinematic performance measures, with greatest sensitivity at lower force fields. This suggests that the form of a force field may play a different "role" for subjects with various impairment levels, and confirms that to achieve optimized therapeutic benefit, it is necessary to personalize interfaces.**

I. Introduction

In conventional therapy, therapists routinely customize and adjust the focus of therapeutic intervention in response to the client's abilities and performance. A review of clinical stroke trials [1] notes that protocols should ideally be personalized for a given patient based on specific deficit, interests and capabilities. Since robotic devices can provide a more objective, precise and repeatable training dosage (e.g. force, intensity, range of motion) than rehabilitation practitioners are able to, it is suggested that there is a great potential to prescribe a more personalized robotic therapy protocol for a given client. However, few robotic therapy studies to date either use a customized intervention protocol or investigate personalized options that are based on evaluating the performance of subjects with various impairment levels.

Perhaps the greater research challenge in customizing a robotic therapy protocol relates to what and how to personalize. This suggests the importance of evaluating performance through goal-directed tasks that vary key interface parameters (e.g. active workspace, force magnitude, intensity), while involving subjects with different impairment levels. Such results may potentially provide a quantitative basis for optimizing these parameters in personalized intervention protocols.

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Trajectory-tracking tasks require common components involved in both perception-action coupling and functional motor tasks: perception of environmental constraints, motor planning and execution, and corrective monitoring of performance including explicit feedback [2]. Several studies have already evaluated the assessment capability of trajectory tracking tasks for subjects with stroke-induced impairments. It has been demonstrated that the motor functional level of subjects and their performance in trajectory-tracking tasks are closely related [3]; furthermore, a kinematic metric (root mean square error, RMSE) derived from trajectory tracking tasks has been demonstrated as a reliable, sensitive assessment tool of the upper-extremity motor function in subjects with stroke-induced hemiparesis [2]. In summary, trajectory tracking clearly affords an effective approach and potentially improved sensitivity for assessing upper-extremity motor function for personalized task settings.

The aim of this study is to evaluate the movement features of human subjects with various levels of stroke-induced impairment for a trajectory-tracking task performed under different task settings. A multivariate model is used to summarize the collective performance of subjects with stroke-induced hemiparesis in trajectory tracking task under varied parameters of force and tracking speed. Our primary goal is to quantify the performance of people with induced hemiparesis in trajectory tracking tasks using various settings for a force reflecting joystick device.

TABLE I. SUMMARY OF PARTICIPANTS INFORMATION

Subject	*Age*	*Gender*	*Impaired side*	*UE-FM (66)*
S1	52	M	L	27
S2	56	F	L	27
S3	60	M	R	33
S4	42	M	R	35
S5	51	F	L	36
S6	55	F	L	45
S7	77	F	L	47
S8	63	M	L	53
9	56	F	R	55
S10	57	F	L	61
S11	58	F	R	63
S12	58	M	R	65
Mean (STD)	*57.1 (8.2)*			*45.6 (13.9)*

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A. Study protocol

Twelve subjects with stroke-induced hemiplegia participated in this study. The upper extremity motor control portion of the Fugl-Meyer (UE-FM) assessment test ([4]) was used to assess the level of upper-extremity motor impairment of subjects (maximum of 66), as summarized in Table I. Exclusion criteria were being under twelve months post-incident, UE-FM score lower than 20, cognitive dysfunction sufficient to limit comprehension of the experimental tasks, and severe concurrent medical problems (e.g. shoulder pain, visual neglect) sufficient to preclude the completion of the goal-directed tasks across the conventional joystick workspace. This study was approved by the Institutional Review Board (IRB) at Marquette University and all the subjects gave informed consent.

A Windows-based human performance assessment package called "UniTherapy" [5], interfaced with a conventional force-reflecting joystick, was used as the experimental platform. As shown in Fig. 1, all subjects were asked to complete the trajectory tracking task under various force field settings: follow the continuously moving target along a circle pattern and stay within the target window as much as possible. Tasks were repeated with a spring-like force field which is generated by:

$$F_{x,y} = K * (\text{Subject}_{x,y} - \text{Target}_{x,y})$$

where $F_{x,y}$ represents the force, K represents the spring index, $Subject_{x,y}$ represents the subject position, and $\text{Target}_{x,y}$ represents the target position. All subjects completed continuous circle tracking tasks under total 15 settings: the repeat of five force-field settings obtained by adjusting the K value of the force-feedback joystick device (100%, 50%, 0, -50%, -100%.) with each of three target speed settings (slow of 20 second/circle, medium of 12 second/circle, and fast of 8 second/circle). For the force settings, the unit of force is the maximum spring force the joystick can yield, with a *positive value providing assistance* and a *negative value providing resistance*. The task was repeated 3 times under each setting, with the sequence of these task settings being randomly arranged by the experimental protocol in order to minimize any "learning effect" on the result.

B. Data analysis

A number of kinematic performance metrics examining accuracy [6], curvature [7], and so on have been developed to characterize movement features in trajectory tracking. The following are presented here:

- *Percentage Time in Target window (PTT):* The percentage of the time the human subject staying within the target window. It is used to characterize accuracy and steadiness.
- *Root Mean Square Error (RMSE):* The squared root of the mean-squared distance from the subject position to the target position. It is a measure of accuracy.
- *Deviation:* The mean of the perpendicular distance from the subject position to the target line within the movement time. It is a measure of curvature.

A multivariate regression model was used to fit the results for these three selected performance metrics (e.g. PTT, RMSE, and Deviation) across subjects and tasks within the same target speed settings, with independent variables being UE-FM score and the force field settings. Coefficient of determination (R^2) was used to select the order of the regression model and further evaluate the fitness of the regression model to the performance results. The 3rd order polynomial model was chosen after evaluating the R^2 value with the different order (e.g. linear, 2nd, 3rd, 4th order) models, with the consideration of both fitness and model simplicity. Of note is that the average R^2 value of the 3rd-ordermodels across three metrics was 99.5% of the R^2 value of the 4^{th-}-order models, while the average R^2 value of the 2nd-order models across three metrics was only 90.5% of the R^2 value of the 3rd-order models.

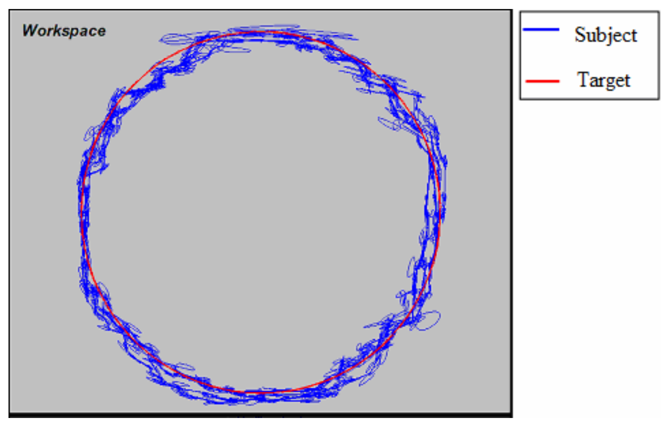

Fig. 1. The example subject position and target position data for continuous circle tracking under spring assistance. The sample is from an able-bodied subject whose data is not reported here.

II. RESULTS

A. Percentage Time in Target window (PTT)

As shown in Fig. 2, regression models fit PTT results better under slow target speed settings. In both dimensions of force-field and UE-FM, the model fits show saturation at both ends and greater sensitivity in the middle range, with the sensitive range varying under different target speed settings. Across models, there is a significant difference in PTT between low and medium/high speed, which suggests that accuracy and stability improved with lower target speeds. Table II provides 3rd-order polynomial regression equation fits for the PTT results under slow, medium and fast target speed settings, with independent variables being Force and UE-FM.

TABLE II: Regression equations for PTT*

Speed	***3rd-order polynomial regression:***
Slow	PTT = 56.48-3.554*u+3.699*f+0.0997*u^2-9.060 *10-6*f^2-7.159*10-4*u^3-1.267*10-5*f^3
Medium	PTT = 57.27- .245*u+0.2908*f+0.1193*u^2+ 1.9855*10-4*f^2-9.439*10-4*u^3-1.267*10-5*f^3
Fast	PTT = 63.84- 244*u+0.2062*f+0.09930*u^2+ 2.852*10-4*f^2-6.704*10-4*u^3-6.865*10-6*v^3

* *u* is the UE-FM score of the subject and *f* is the force magnitude.

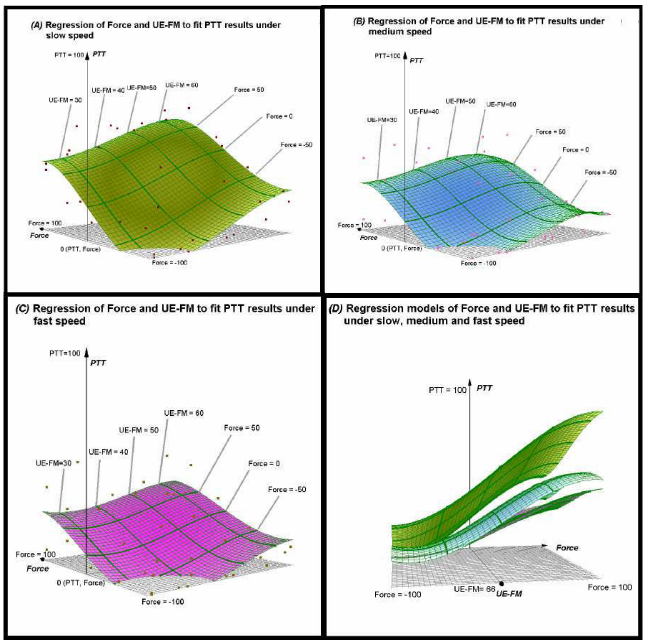

Fig. 2. Regression models to fit PTT results as a function of Force-Field and UE-FM, under slow speed (*A, R^2=0.86*), medium speed (*B, R^2=0.74*), and fast speed (*C, R^2=0.67*) settings. All 3 models are overlapped in (*D*), highlighting Force-Field axis. The thicker lines on the regression surface represent [UE-FM = 30, 40, 50, 60; Force = -50, 0, 50].

B. Root Mean Square Error (RMSE)

As shown in Fig. 3, regression models fit RMSE results better under slow target speed settings. General findings for all three models are that in both dimensions of force and UE-FM, the models saturated in both ends and showed better sensitivity in the middle (low-to-moderate force) range, with the sensitive range varying under different target speed settings. Table III provides 3rd-order polynomial regression equations that are used to fit the RMSE results under slow, medium and fast target speed settings, with independent variables being Force and UE-FM.

TABLE III: Regression equations for RMSE*

Speed	***3rd-order polynomial regression:***
Slow	RMSE = -26.01+3.617*u-0.1041*f-0.09416*u^2+ 0.0007287*f^2+6.948*10-4*u^3-1.408*10-6*f^3
Medium	RMSE = -74.92+7.425*u-0.1657*f-0.1844*u^2+ 6.777*10-4*f^2+1.375*10-3*u^3+5.574*10-6*f^3
Fast	RMSE = -55.44+5.929*u-0.1636*f-0.1439*u^2+ 4.314*10-4*f^2+1.039*10-3*u^3+4.633*10-6*f^3

* *u* is the UE-FM score of the subject and *f* is the force magnitude.

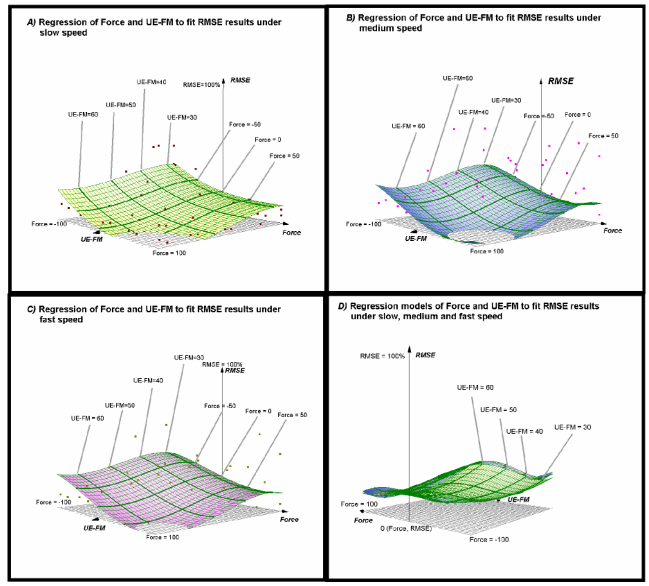

Fig. 3. Regression models to fit RMSE results as a function of Force-Field and UE-FM, under slow speed (*A, R^2=0.69*), medium speed (*B, R^2=-.60*), and fast speed (*C, R^2=0.60*) settings. All three regression models are overlapped in (*D*). The thicker lines on the regression surface are presented in the case of [UE-FM = 30, 40, 50, 60; Force = -50%, 0%, 50%].

C. Deviation

As shown in Fig. 4, the general findings for deviation are that in the dimension of force field, the models saturated in the assistance end and showed better sensitivity in the resistance end under different target speed settings. This suggests that the deviation metric is more sensitive to the resistance force field, and less sensitive to the magnitude of the assistance force field (i.e., even mild force-field assistance is beneficial for this metric). Table IV provides 3rd-order polynomial regression models that are used to fit the curvature results under slow, medium and fast target speed settings, with independent variables being Force and UE-FM.

TABLE IV: Regression equations for Deviation*

Speed	*3rd-order polynomial regression:*
Slow	Deviation = -21.73+1.902*u-0.03354*f-0.04501*u^2+ 3.489*10-4*f^2+3.172*10-4*u^3-1.022*10-6*f^3
Medium	Deviation = -45.85+3.671*u-0.04797*f-0.08473*u^2+ 3.328*10-4*f^2+6.010*10-4*u^3+2.639*10-7*f^3
Fast	Deviation = -31.67+2.771*u-0.06169*f-0.06386*u^2+ 2.545*10-4*f^2+4.409*10-4*u^3+1.511*10-6*f^3

* u is the UE-FM score of the subject and f is the force magnitude.

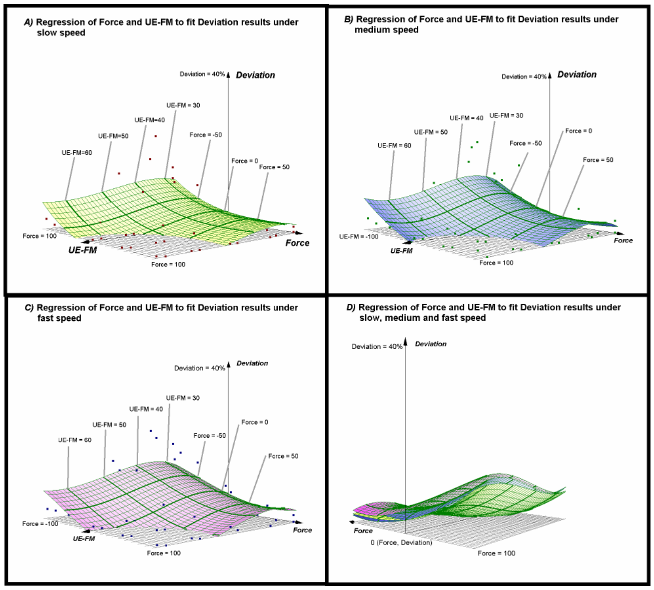

Fig. 4. Regression models to fit Deviation results as a function of Force and UE-FM, under slow speed (*A*, $R^2=0.59$), medium speed (*B*, $R^2=0.58$), and fast speed (*C*, $R^2=0.61$) settings. All three regression models are overlapped (*D*). The thicker lines on the regression surface are presented in the case of [UE-FM = 30, 40, 50, 60; Force = -50%, 0%, 50%].

III. Discussion and Conclusion

Regression models of selected kinematic metrics fit the results for a group of subjects with remarkably diverse abilities quite well, as measured by coefficient of determination (R^2) within the range [0.582, 0.855]. These regression models showed non-linear effects in both force field magnitude and impairment level on these metrics with various sensitive and saturating regions, suggesting that even small "assist" and "resist" force-fields affect task performance. Interestingly, 2 of the 3 metrics (RMSE, Deviation) were less sensitive to speed, with PTT sensitive in a predictable way.

As might be expected, across subjects with various impairment levels, providing assistance force will improve the performance of accuracy (PTT, RMSE), steadiness (PTT) and path deviation (deviation) in the trajectory tracking tasks, while the resistance force will decrease performance of these movement features. For both PTT and RMSE, the regression models saturated in both ends and showed better sensitivity in the middle force range, with the sensitive range varying under different tracking speed settings.

These findings suggest that the magnitude of force assistance generated by commercially available joysticks, although of a smaller scale compared with the large "rehabilitator" robotics, can significantly vary movement performance features across human subjects. Furthermore, the clear trends towards saturation shown at the end of assistance force settings suggests that any additional increase of the force would have yielded diminishing sensitivity in terms of changes in performance (e.g. accuracy, steadiness). For deviation, the regression fits for force sensitivity all saturated in the assistance end and then showed better sensitivity in the resistance end across different tracking speed settings. This finding suggests that assistance force won't improve the path deviation performance significantly across human subjects with various impairment levels. However, resistance force may continue to cause significant changes in the performance of path deviation.

An overall implication is that small motors, such as those used in the mass-marketed commercial force-reflecting joysticks, are sufficient for providing forces within the range where there is highest sensitivity to performance variation. This conclusion should be taken cautiously, with the consideration of the various sources of the error (e.g. force, UE-FM scores) and also that the protocols only included a limited number of force levels and a self-selected location for the joystick relative to the participant (which was maintained throughout the session).

More broadly, our results suggest that the form of a haptic interface plays a different "role" for subjects with various impairment levels. This helps confirm that it is necessary to customize the interface based on an individual's impairment level.

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