Modeling Upper Limb Clinical Scales by Robot-Measured Performance Parameters

R. Colombo, I. Sterpi, A. Mazzone
Bioengineering Service
Fondazione Salvatore Maugeri, IRCCS,
Rehabilitation Institutes of Pavia and Veruno(NO), Italy
roberto.colombo@fsm.it

F. Pisano, C. Delconte
Neurologic Rehabilitation Dept.
Fondazione Salvatore Maugeri, IRCCS,
Rehabilitation Institute of Veruno(NO), Italy

Abstract—**The status of motor function in stroke survivors and the effect of any therapeutic intervention are generally measured by physiotherapists using clinical assessment scales that probe specific aspects of a subject's motor behavior. Although they are widely accepted, these measurement tools are limited by interrater and intrarater reliability and are time-consuming to apply. This paper analyzes the changes in movement kinematics and kinetics during robot-aided neurorehabilitation of subjects after stroke and verifies the possibility of estimating outcome measures by means of a set of robot measured parameters.**

Keywords-component; Outcome Measures, Robot therapy, Neurorehabilitation, Stroke.

I. INTRODUCTION

A recent systematic review literature has analyzed the effects of robot-assisted therapy on the recovery of upper limb after stroke, demonstrating its capability to improve short and long term motor control even if no consistent influence on functional abilities was observed [1-3]. In addition a multicenter study demonstrated that robot-assisted therapy improved outcomes over 36 weeks [4]. The status of motor function in stroke survivors and the effect of any therapeutic intervention are generally measured by physiotherapists, using clinical assessment scales that probe specific aspects of a subject's motor behavior [5-9]. They are standardized and validated but nevertheless, being administered by humans, they may lack in reliability. The measurement obtained is always subjective and depends on the ability of the rehabilitation professional. Robot devices have built-in technology to measure displacements, velocities, forces and quantify other derived parameters [10-12]. These measures have the benefit of being objective, reproducible and capturing different aspects of the motor improvement. Therefore, they may be successfully employed both for training and evaluation purposes. In particular, the sensors equipping rehabilitation robots allow an accurate measurement of movement kinematics (i.e. the trajectories of the limbs) and kinetics (the forces involved), which can be used to derive measures related to upper-extremity movements. These objective measures can be computed automatically during therapy to provide information about a subject's motor impairment and functional ability. Therefore, they could be used to assess motor functions more frequently.

Other works have tried to clarify how these robot-based kinematic and kinetic metrics relate to traditional human-administered clinical scales for measuring outcome. In particular our research group introduced some models to describe the performance acquisition pattern during robot training (i.e. how these movement measures change with time). and demonstrated that the simultaneous assessment of kinematics and kinetics improvements during training could provide new insights into the mechanisms of recovery [10,11]. In addition, two other papers reported a strong to moderate correlation between normalized and non normalized movement quality measures obtained by the robots during training and standardized clinical scales [13,14]. This paper aims to analyze the changes in movement kinematics and kinetics during robot-aided neurorehabilitation of subjects after stroke and describes their relationship with the outcome measures.

II. METHODS

Eighteen patients after stroke (age=52± 13 yrs; gender=6F,12M; paretic arm=10 left, 8 right) were included in this study performed at the Salvatore Maugeri Foundation, IRCCS Rehabilitation Institute of Veruno (Veruno, NO, Italy). All patients were in chronic stage, their unilateral cerebrovascular accident (CVA) having occurred at least 6 months prior to enrolment (22 ± 20 months from CVA). Inclusion criteria were the presence of a single unilateral CVA and the presence of at least 10° of motion in the treated joints. Subjects with severe sensory and visual field impairment and aphasia were excluded. The study was carried out in conformity with the Declaration of Helsinki of the World Medical Association; all patients gave their informed consent to participate in the study, which was approved by the local scientific and ethics committees. Patients' performance in kinetic parameters was compared with that of a group of 7 healthy subjects (age: 41.7 ± 8.8 years). Patients were trained by means of the shoulder-elbow manipulator MEMOS (MEchatronic system for MOtor recovery after Stroke). a complete description of the system has been reported previously [11,12].

A. Experimental procedure

Patients were seated in a chair and had their trunk fastened to the back of the chair by a special jacket in order to limit compensation phenomena. The patient's paretic limb was supported at the elbow by a low friction pad that slid along the surface of the robot workspace. The starting and target points of reaching were presented on a computer monitor situated above the robot workspace. Patients had to make a sequence of point-to-point reaching movements in the horizontal plane; they were instructed to move the robot handle from the starting point to the end point following the straight line connecting them. Typical trajectories consisted of a square, or more complex geometrical figures including diagonal movements. Visual feedback of the current position of the handle was provided by means of a different coloured target. No assistance was provided during voluntary movements. If the patient could not complete the movement by means of voluntary activity, the robot evaluated the current position and guided the patient's arm to the target position. Patients received robot training twice a day, 5 days a week for at least three weeks. Each training session consisted of 4 cycles of exercise lasting 5 min. each followed by a 3 min. resting period. A practice session with detailed instructions was administered before training, in order to minimize the exercise learning effect.

B. Clinical measures

Patients' abilities were assessed using the Fugl-Meyer scale (FM; range: 0-66) [15], and Motor Status Score (MSS; range: 0-82) [16] at the start and end of treatment. In this study we used only the upper limb section of the FM scale. It is able to detect changes due to motor recovery in patients with severe to moderate motor impairment after stroke. The MSS was developed at the Burke Rehabilitation Hospital and is characterized by a greater sensitivity thanks to its 40-point score range for isolated shoulder and elbow movements specifying the quality of voluntary movement in the hemiparetic upper limb.

C. Parameters measuring movement kinematic and kinetics

In this study we used both kinematic and kinetic measures of upper limb movements, taken at the robot end-effector. Kinematic measures quantify the spatial and temporal quality of a subject's movement. Kinetic measures are usually used to quantify force, work, energy consumption and power associated with a subject's motor behaviour. The following parameters were considered:

Movement smoothness. According to Rohrer et al. [17] movement smoothness can be evaluated by means of five parameters related in different ways to the movement speed of the manipulator during active movements. In our study the smoothness was obtained by computing the number of peaks in the tangential speed profile (local maxima found in the signal, low pass filtered at 3Hz) of each reaching movement. If a point-to-point reaching movement has a lower number of peaks in speed profile than in another movement this means that fewer acceleration and deceleration periods are present. The number of peaks is expressed as a negative value so that increases in the peak metric equal increases in smoothness.

Movement speed. The robot device allowed to record the current position of the handle. In this way the mean value of the velocity (MV) of the handle during the task execution could be computed. The mean speed may be considered a measure of smoothness; in fact several papers have shown that the movement during a motor task is the combination of a sequence of sub-movements with a bell-shaped velocity profile [18]. In addition it has been demonstrated that such components are clearly distinct at the beginning of treatment (jerky movements) so resulting in a low mean velocity value, and tend to merge in the course of treatment so producing a smoother movement and higher values of speed [17,19]. On the other hand, if a patient moves slowly, without a lot of variation in the speed profile, while another one starts and stops frequently, and attains the same mean velocity, the resulting smoothness values should be quite different. For this reason, given the many-faceted aspects represented by the mean velocity, we decided to consider this metric as a distinct component of motor recovery.

Normalized force control parameter. The robot system we used includes a force transducer providing the patient's exerted force in the displacement direction. In particular it provides its components f_x and f_y in the orthogonal directions (front to back and lateral) of the two degree-of-freedom workspace. If we consider a graphic representation of the force components in a normal subject, when the motor task consists of four reaching movements corresponding to the four edges of a square, the picture obtained is similar to that obtained in figure1a. If we are interested only in how the subject is
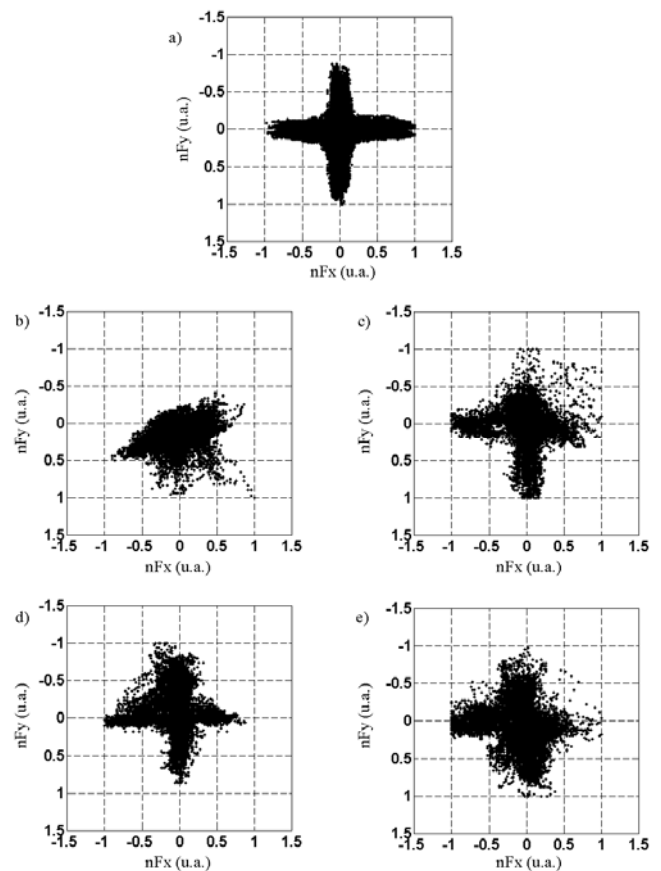

Figure 1. Example of distribution pattern of the normalized force components in 7 normal subjects. (a=average pattern), and in two poststroke patients at the start (b,c) and end (d,e) of treatment.

directing the force, the force values can be normalized by their respective maximum value, so obtaining a graph expressed in the ±1 range for each component. We can note that the pattern of distribution of the force values are approximately aligned along the two preferential directions of reaching. If we try to draw the same picture for a patient executing the same task (square tracing) at the start (figure1 b, c) and at the end (figure1 d, e) of treatment, we observe that the distribution pattern of the force values at the start of training does not show preferential directions of distribution as conversely happens in the end-training picture. A force control parameter (nFCP) was obtained by computing the similarity of the distribution pattern obtained during a training session to the reference pattern, obtained by averaging the force distribution pattern of seven normal subjects executing the same reaching task as post-stroke patients. In practice the comparison consisted in computing the difference between two images - the patient force distribution and the reference distribution obtained in the normal subjects group - and performing a double-integration of the obtained image-difference along its two dimensions. The parameter is expressed as a percentage of the whole image dimension. It can be considered as a parameter measuring the amount of error in the orientation of the exerted force during the task execution; therefore decreasing values during training reflect an improvement in force control during task execution.

Force directional error. The Force Directional Error (FDE), defined by Lum [20,21], is the angle between the force vector recorded by the MIME robotics device and the unit vector aligned with the theoretical direction of movement. This angle is calculated at each sampling point and averaged across the trajectory. The 2 DoF robotic device we used constrained movement within the horizontal plane, but let the patient free to move the robot handle in any direction of the workspace, creating a trajectory based on the applied force. For this reason in our case the angle considered was that formed between the vector aligned with the movement direction made by the patient and the vector aligned with the theoretical direction of movement (i.e. the line joining "start" and "end" positions of the reaching movement). Here, we considered as movements in the target direction only those in which the condition $|\theta| \leq \pi/2$ was met. In order to obtain, the FDE value over a whole training session, we computed the mean value from all reaching movements of the training session.

Data analysis and statistics. The robot measured parameters were evaluated only during the active phase (i.e. without assistance) of movement. Student's t-tests for repeated measures were conducted to verify the statistical significance of change of movement kinematics, kinetics and of clinical variables in post-treatment with respect to pre-treatment values. In particular the pre and post treatment robot-measured parameters were obtained by averaging the values obtained during the first and last three training sessions. The time course of variables was assessed by the fitting of an exponential decaying law for the analysis in the whole group. The relationship between the clinical variables and the robot-measured variables was assessed by backward stepwise regression analysis. Statistical analysis was performed using the StatView statistical package (SAS Inst., NC-USA).

III. RESULTS

A. Changes of movemen kinematics and kinetics during treatment

The movement kinematics and kinetics of the robot-treated patients measured by means of the above reported parameters, improved during the course of treatment. Table 1 summarises the mean values ± standard deviations of PRE and POST treatment variables, their changes and the p value of the PRE vs. POST comparison. The parameters showed a statistically significant decrease in our group of chronic subjects after stroke. In particular 15 of the 18 patients decreased both nFCP and FDE, 3 increased the nFCP parameter and one increased both nFCP and FDE. Only 12 of these patients showed an improvement in the FM scale while 17 showed an improvement in MSS

TABLE I. PRE AND POST TREATMENT VALUES OF THE MOVEMENT KINEMATIC AND KINETIC MEASURES

	PRE	POST	Change	p
VM (mm/s)	39.61±16.45	63.15±15.91	23.54±16.96	< 0.0001
SM (-nPK)	-15.19±7.54	-6.43±5.78	8.76±6.82	< 0.0001
nFCP (a.u.)	30.23±6.23	22.26±6.15	-7.97±7.83	0.0001
FDE (deg)	30.61±9.48	21.43±5.77	-9.17±8.59	0.0005

B. Modeling time course of recovery

The a) and b) panels of figures 2 show the time course of mean velocity (MV) and movement smoothness (SM), the two parameters describing the movement kinematics, during 32 training sessions in the group of chronic patients treated with our robot device. Each point represents the average value obtained by the group for each training session. The vertical bars represent the standard error. It can be seen that the performance acquisition follows an increasing exponential law,
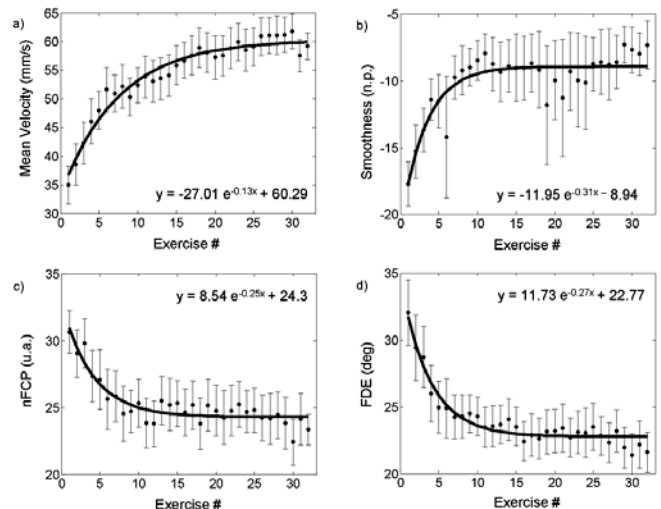

Figure 2. Values of the mean velocity, movement smoothness, nFCP and FDE over the course of 32 training sessions of therapy in the group of patients after stroke. Each point represents the average value obtained by the group for each training session. The vertical bars represent the standard error. The overlapped curve is the exponential decaying model fitting the parameter's values obtained during the training.

so allowing the computation of the time constant related to the exponential improvement. The time constant was 7.7 sessions for MV and 3.2 sessions for SM. A plateau was reached towards the end of treatment for MV and after about 12 training sessions of robot treatment for SM. The fitted model had a very high correlation with the data (r= 0.98 for MV ; r=0.87 for SM).

The c) and d) panels of figures 2 report the time course of nFCP and FDE. Also in this case, the directional error of the patient exerted force decreased as treatment progressed and the average acquired performance followed a decreasing exponential law that allows the computation of the time constant related to the exponential decay. The time constant was 4.0 sessions for nFCP and 3.73 sessions for FDE. In both parameters the plateau was reached after about 15 training sessions corresponding to 1.5 weeks of robot treatment. The fitted model had a very high correlation with the data (r= 0.92 for nFCP ; r=0.96 for FDE).

C. Modeling clinical variables by robot-measured performance parameters

The modeling of the relationship between the patient's motor performance and the clinical scales was detailed in the second part of the study conducted on the same group of patients after stroke.

The model considered the pre and post treatment values of the MV, SM, nFCP and FDE motor performance parameters as independent variables, and the pre and post treatment values of FM scale and MSS respectively as dependent variable.

Table II summarises the mean values ± standard deviations of pre and post treatment clinical variables and the p value of the pre vs. post comparison. Findings show that our chronic patients reduced their impairment after treatment with the robot. Table III summarises the r, r2 and p values of the regression analysis carried out to model the relationship between the Fugl-Meyer scale and the Motor Status Score by the robot measured variables (pre and post treatment values).

The models fitted by the stepwise regression including all the robot measured parameters were represented by the following formulas:

$$FM= 41.419 - 0..687*nFCP$$

$$MSS= 53.178 - 0.893*nFCP$$

The MSS variable showed lower r values than those obtained for the Fugl-Meyer scale. Only the nFCP variable made a significant contribution to the model.

A second model was fitted to assess the relationship between the changes obtained in the robot measured variables, the clinical variables at the start of treatment and the clinical outcome (i.e. the clinical variables at the end of treatment). In practice, the model considered the changes in MV, SM, nFCP and FDE and the FM or MSS values at the start of treatment as independent variables and the clinical scale values (FM or MSS) at the end of treatment as dependent variables. Table IV

summarises the r, r2 and p values of the regression analysis carried out to model the relationship.

The models fitted by the multiple regression were represented by the following formulas:

$$FM_{POST}= 0.817 - + 1.131 *FM_{PRE}$$

$$MSS_{POST}= 1.856 + 1.093* MSS_{PRE}$$

The modeling results show very high correlation and r-square values in both clinical scales. In particular the correlation was greater than 0.95, but the changes in robot measured parameters did not contribute to this model.

TABLE II.   PRE AND POST TREATMENT CLINICAL VARIABLES

	PRE (mean±sd)	POST (mean±sd)	p
Motor Status Score (MSS, range:0-82)	27,53±12,44	31,94±14,07	<0.001
Fugl-Meyer (MS, range:0-66)	21,44±8,58	25,06±10,04	<0.001

TABLE III.   **MODEL1:** MULTIPLE REGRESSION RESULTS BETWEEN CLINICAL SCALES, AND ROBOT MEASURED VARIABLES (PRE AND POST TREATMENT VALUES)

	Significant Independent Variables nFCP		
Dependent Variables	r	r^2	p
FM	0.561	0.315	<0.001
MSS	0.492	0.242	<0.03

TABLE IV.   **MODEL2:** MULTIPLE REGRESSION RESULTS BETWEEN PRE-TREATMENT CLINICAL SCALES, ROBOT PARAMETERS CHANGES (Δ=POST-PRE) AND POST-TREATMENT CLINICAL SCALES

	Significant Independent Variables FM(MSS)PRE		
Dependent Variables	r	r^2	p
FM	0.967	0.935	< 0.0001
MSS	0.966	0.933	< 0.0001

IV.   DISCUSSION AND CONCLUSIONS

The results presented here confirm that the neural adaptation resulting from robotic training may improve both movement kinematics and kinetics. Assessment of the time course of recovery showed that nFCP, FDE and the movement smoothness improve quickly at first and then plateau, while steady gains in mean velocity occur over a longer time. The model developed to assess the relationship between the robot measured variables and the clinical scales showed a moderate correlation. This is in line with results obtained in our previous studies and could be due to the fact that the improvement in clinical scales is related to many other variables that may have no direct relationship with the improvement of movement dynamics acquired during planar tasks. However, the topic is of course relevant in that the objective is to provide researchers and therapists with a standardized and reliable tool to evaluate

patient outcomes with a set of objective, quantitative and highly repeatable measurements. The second model estimating patient outcome based on the motor improvement measured by the robot and the clinical scale values at the start of treatment, showed a strong correlation value. This is due solely to the strong relationship between pre and post treatment values without any significant contribution coming from the changes obtained in the robot measured parameters. Therefore it may be considered more useful to save resources (the time required for carrying out the second evaluation) in outcome estimation. The performance of regression models, relating robotic and clinical assessments, generally decreases when the models are tested on an independent data set for model validation [14]. Because of the limited number of subjects included in the study no validation of the fitted models has been provided in this study. Thus future extension of this work will include a validation procedure using an independent data set in order to demonstrate the real potential of these models.

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