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Quantitative evaluation of upper-limb motor control in robot-aided rehabilitation

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Abstract This paper is focused on the multimodal analysis of patient performance, carried out by means of robotic technology and wearable sensors, and aims at providing quantitative measure of biomechanical and motion planning features of arm motor control following rehabilitation. Upper-limb robotic therapy was administered to 24 community-dwelling persons with chronic stroke. Performance indices on patient motor performance were computed from data recorded with the InMotion2 robotic machine and a magneto-inertial sensor. Motor planning issues were investigated by means of techniques of motion decomposition into submovements. A linear regression analysis was carried out to study correlation with clinical scales. Robotic outcome measures showed a significant improvement of kinematic motor performance; improvement of dynamic components was more significant in resistive motion and highly correlated with MP. The analysis of motion decomposition into submovements showed an important change with recovery of submovement number, amplitude and order, tending to patterns measured in healthy subjects. Preliminary results showed that arm biomechanical functions can be objectively measured by means of the proposed set of performance indices. Correlation with MP is high, while correlation with FM is moderate. Features related to motion planning strategies can be extracted from submovement analysis.

Keywords Robot-aided rehabilitation ·
Motor assessment

1 Introduction

The use of robotic machines as a possible rehabilitation strategy to achieve motor recovery can be justified by its impact on better therapeutic treatment and motor learning. Deeper knowledge on the mechanisms of neurogenesis, stimulated by voluntary movements during motor training [20, 22, 33], and neuroplasticity, underlying the motor learning and the functional recovery after cerebral injury [13, 41], points out the potential of robotic technologies to create a real discontinuity in the clinical procedures of the (neuro)rehabilitation treatment. Learning or re-learning is a necessary condition for true recovery as well as for compensation [23] and can be stimulated and shaped by rehabilitation [27, 28, 53].

Robotics can greatly contribute to produce novel and cost-effective solutions able to significantly improve the outcome of the rehabilitation process or assist in coping with residual abilities after the rehabilitation process. The benefit of using robotic machines is multiple [8, 15]. Robotic machines can contribute to: (i) Technological evolution of machines for physical exercise as well as for cognitive training [4, 16]. (ii) Significant reorganization of the working procedures within the rehabilitation process. Machines can take over most of unpleasant and physically demanding tasks, leaving to the healthcare operators the possibility to mainly concentrate on the quality of the

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therapy that is delivered. (iii) New therapeutic approaches, based on a deep-and-long-lasting stimulation [32]. Robotic machines can allow assisting also subjects with low residual motor abilities, and help them start and complete motor tasks when they are not able to do that, directly monitoring their motion intention. (iv) Cortical reorganization in patients affected by stroke or other neuromotor pathologies [41] and increased habitual use of the hemiparetic arm in activities of daily living [5]. Such an approach is highly repetitive, intensive, structured, and based on the central role of the patient all along the different phases of the motor exercise. (v) Evidence-based rehabilitation. Robotic machines can also provide quantitative and very accurate measurements of patient performance during the execution of a motor task. Robot data can be used for rigorous and objective assessment of the therapeutic approach and provide an important empirical evidence for basic research on neuroplasticity phenomena.

In spite of the wide literature on the first four issues, mainly concerned with the design and development of robotic devices and their validation in clinical settings, current literature is still poor of works on the fundamental role played by robotic technologies in evidence-based medicine (see [5, 35, 42, 53] for a review). Modern medicine is based on objective evaluation and quantitative comparative analysis of the impact of different therapeutic approaches. Robotic technology provides accurate, precise, and very sensitive tools for assessing and modeling human behavior, well beyond the capability of a human observer. This is of paramount importance for enabling appropriate initial diagnosis and early adoption of corrective clinical strategies, and for identifying verifiable milestones as well as prognostic indicators of the recovery process.

Recently, the first examples of evaluation metrics based on robot data were provided [3, 7] for quantifying motor recovery of stroke patients undergone robot-aided rehabilitation. Moreover, studies on movement smoothness [17, 24, 45] were proposed in the last years, using kinematic data recorded by the robot for analyzing motion characteristics of unimpaired patients. However, they were both limited to characterization of patient kinematics during unperturbed point-to-point motion, where no active force regulation was required and no other sensory system (in addition to the robot) was used for assessment.

In this paper a preliminary study of multimodal analysis of patient performance is proposed that combines robotic technology with wearable sensors to provide a quantitative measure of kinematic, dynamic, and motion planning features of upper-limb motor control. To this purpose, a set of indices originated from robot data and presented in our pilot study in [57] on a limited number of patients is used to characterize kinematic and dynamic performance of a wider population of stroke patients in unperturbed motion

as well as resistive motion, where active force regulation is required to successfully achieve the motor task. In addition, a new assessment tool of subject planning functions is proposed, which is grounded on the study of human mechanisms of motion generation.

Several studies point out that human motion can be decomposed in elementary units, named submovements [43], probably originated by a "neural controller" in the brain [1, 10, 12, 30, 36, 37, 39, 40, 55]. Like primitives in natural and computer languages can be combined to generate a grammar of more complex constructs, the central nervous system can combine these elementary units to generate a manifold of more complex motor behaviors.

Our preliminary works on this topic [46, 56] provided new insights into the existence of a neural controller embedded in the brain that is *discrete*, works *rhythmically*, and *sequentially* sends pulse signals (i.e., submovements) at a specific sample rate to each limb segment, modulated in accordance with limb intrinsic inertia and muscle recruitment method. The change of submovement features with stroke and with recovery can provide evidence of how the neural controller embedded into the brain is affected by the pathology and modifies with the therapy.

In this study, a robot-aided motor therapy of the upper limb was administered to 24 chronic post-stroke patients. Two robotic machines were used for delivering therapy: the InMotion2 [18] and the InMotion3 [26]. Patients underwent a double body functions evaluation: the first one was based on Fugl-Meyer (FM) and Motor Power (MP) clinical impairment scales; the second one was based on the core set of kinematic and dynamic indices in [57], extracted from the InMotion2 planar machine data, and a new set of indices on motion planning features grounded on the submovement composition theory and extracted from acceleration data (which were measured by a magneto-inertial sensor on the patient hand).

Results of the quantitative upper-limb assessment are reported in the paper. Robot-based assessment was applied to all 24 patients and a correlation analysis with clinical scales was also carried out. The study on human motion generation based on the rhythmic composition of submovements was developed later. Consequently, it was preliminarily applied to a comparison group of five healthy subjects and to five post-stroke patients. An extension of the study to the 24 post-stroke subjects is envisaged.

2 Methods

2.1 Subjects

The experimental protocol was approved by Local Ethical Committee; experiments were performed according to the

Table 1 Patients anamnestic data and FM and MP scores at admission and discharge

Subject no.	Age	Sex	Type stroke	Months after stroke	Affected side	FM/66 Adm	FM/66 Disch	MP Adm	MP Disch
1	57	M	Ischemic	16	Right	9	14	29	32
2	53	M	Ischemic	22	Left	8	12	28	31
3	37	F	Ischemic	14	Left	24	34	35	42
4	74	M	Ischemic	60	Left	32	39	36	41
5	63	F	Ischemic	7	Left	36	43	38	44
6	45	F	Ischemic	9	Left	13	21	37	42
7	62	M	Ischemic	60	Left	20	25	38	43
8	46	M	Ischemic	24	Right	9	13	23	26
9	84	F	Ischemic	54	Right	35	42	32	36
10	68	M	Ischemic	18	Left	19	26	33	38
11	70	M	Ischemic	24	Right	36	44	36	43
12	68	M	Ischemic	62	Left	9	13	26	29
13	36	M	Ischemic	7	Right	16	24	39	45
14	66	M	Ischemic	8	Right	31	39	40	46
15	36	F	Ischemic	42	Left	19	25	38	43
16	35	M	Ischemic	22	Left	24	31	39	45
17	48	F	Ischemic	110	Left	32	39	36	41
18	83	M	Ischemic	8	Left	21	27	32	37
19	63	F	Ischemic	64	Left	17	23	33	39
20	36	F	Ischemic	60	Right	35	43	38	44
21	36	F	Ischemic	38	Left	21	28	39	46
22	38	M	Ischemic	62	Left	23	30	42	48
23	50	M	Ischemic	40	Right	33	40	42	50
24	59	M	Ischemic	24	Left	11	16	35	40

institutional guidelines for patient studies and with written consent of the patients. Twenty-four community-dwelling persons with chronic stroke (15 men, 9 women) met inclusion criteria and volunteered to participate. Inclusion criteria were the following: (1) diagnosis of a single, unilateral stroke at least 6 months prior to enrollment verified by brain imaging; (2) sufficient cognitive and language abilities to understand and follow instructions (Mini-Mental Status Score of 22 and higher); (3) stroke-related impairments in muscle strength of the affected arm between grades $\geq 1/5$ and $\leq 3/5$ on the MP scale (muscular strength in the biceps, triceps, and anterior, and lateral deltoids were measured); (4) stable condition in motor impairment scale assessed by three consecutive evaluations, 1 week apart, after baseline assessment.

Patients ranged in age from 35 to 84 years (mean $\pm$ standard deviation, 55.9 ± 15.4 years) with an average time post-stroke of 35.6 ± 26.1 months (Table 1). Eight subjects had a history of right-hemisphere stroke; 16 had left-hemisphere damage. None of the subjects were engaged in conventional occupational or physical therapy programs during the experimental trials, and none had received robotic therapy before this research. All subjects

gave informed consent to take part in the study that was approved by local scientific and ethical committees.

For the study on the submovement composition strategy, due to the lack of previous works in the literature on the same approach, a comparison group was required. Five healthy volunteers (3 females, 2 males) with normal vision capabilities or vision that was corrected to normal, ranging in ages from 61 to 74 years (mean $\pm$ standard deviation, 65.2 ± 6.1 years) participated in the experiments. All the subjects were right-handed and were naïve to the purpose of the protocol. Analogously, the study on pathological subjects was preliminarily carried out on five chronic stroke patients answering inclusion criteria described above.

2.2 Robots and sensory system

The two robotic machines InMotion2 and InMotion3 (Interactive Motion Technologies, Inc.) were used to deliver robotic therapy.

The InMotion2 robot (Fig. 1a) is based on a direct-drive five-bar-linkage SCARA mechanism that provides two translational degrees of freedom for shoulder and elbow

Fig. 1 InMotion2 (a) and InMotion3 (b) robotic machines
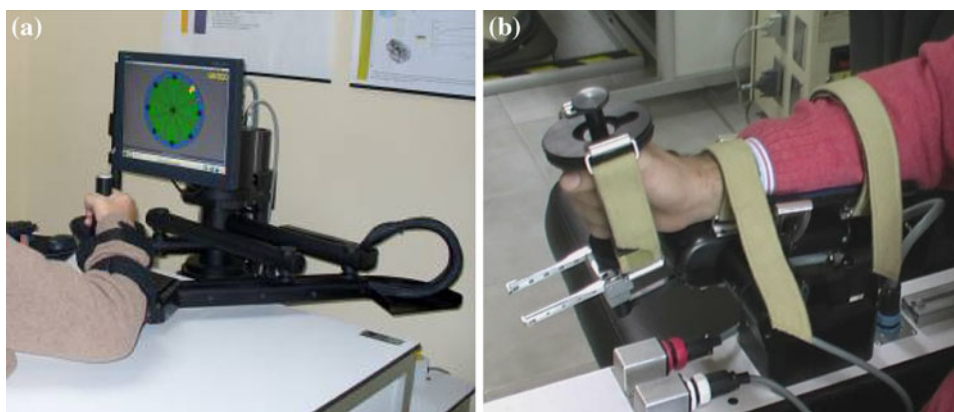
motion. Absolute encoders at each motor and a 6-axis force/torque sensor at the end effector allow measuring robot joint positions and interaction forces, respectively.

The InMotion3 (Fig. 1b) is a robotic device for the wrist rehabilitation. A differential mechanism mounted on a parallelogram linkage and driven by geared actuators provides wrist extension–flexion and abduction–adduction, and pronation–supination.

One robotic machine (i.e., InMotion2) and one magneto-inertial sensor (i.e., Xsens MTx-28A##G##) mounted at the robot end effector were used for quantitative assessment of patient motor control.

Robot-based evaluation was limited to the planar machine because of the twofold motivation of (i) demonstrating the feasibility and the validity of the proposed approach, based on objective kinematic and dynamic measures to assess patients body functions; (ii) comparing our results with current literature, which still lacks of significant clinical studies on distal upper-limb districts. An extension of the work to distal movements is, however, envisaged.

2.3 Experimental protocol and assessment

All subjects were administered with 6 weeks of shoulder–elbow therapy and 6 weeks of wrist therapy, for 12 weeks total of robot-aided therapy. Subjects were randomly assigned partly to shoulder–elbow therapy first and partly to wrist therapy first. They received approximately 1 h of robotic therapy three times a week.

Training consisted of three games of 320 "assisted-as-needed" point-to-point movements from the center to eight outbound targets distributed along a circle at a distance of 0.14 m. Patients were required to move with a self-paced speed in a maximum time slot of 3 s. The assistance was tuned based on patient's performance [25]. In wrist training, the first two assisted games trained wrist flexion/extension, abduction/adduction, and combination of these

movements. The last assisted game exercised exclusively pronation and supination [26].

A paired Student t test was used to verify that the two groups were comparable at admission to as well as at discharge from the robotic therapy (i.e., no statistical significant difference between them), independently of the specific training order. Due to the lack in the literature of a systematic analysis of the possible set of motor measures that can significantly describe kinematic and dynamic changes of patients' body functions following robotic therapy, attention is mostly focused on demonstrating the efficacy of the proposed assessment tools more than on the clinical result on the order effect on patient recovery of proximal vs distal training, which will be addressed in future works. Accordingly, evaluation was carried out on the 24 patients at admission to and discharge from the robotic treatment, over a timeframe of 12 weeks, independently of the training order. It consisted of three main steps.

The first one was a traditional clinical impairment assessment based on upper-limb FM [9] and MP [14, 34] clinical scales.

The second step consisted of performing unperturbed and resistive motion exercises with the InMotion2 robotic machine. The robot was completely passive while position and force sensors recorded subject kinematic and force data. Each subject was asked to perform five blocks of unassisted 16 point-to-point movements in the free space (in the following shortly named unperturbed motion) and, subsequently, one block of 16 point-to-point movements in presence of a force field generated by the robot (in the following shortly referred as resistive motion). The force field can be modeled as a visco-elastic force field applied against patient motion. It is generated by means of a proportional-and-derivative control (with constant gains) pushing robot end effector to the central position of the workspace. The number of resistive movements was lower than the unperturbed movements due to the major level of

fatigue required by the task, but high enough to have a significant set of trials.

The third step (specifically addressed to study submovement composition in reaching movements) consisted of performing one block of 20 unassisted point-to-point movements in one direction with the joint use of the In-Motion2 robotic machine and the magneto-inertial sensor mounted at the robot end effector. Subjects were asked to accomplish the task as fast as possible.

The comparison group was required just to perform the point-to-point exercises of the third step.

2.4 Data analysis

2.4.1 Indices related to biomechanical features

Hand position, velocity, and interaction force Cartesian components were online recorded during each evaluation session through robot sensory system.

Robot data were offline processed to compute the set of five quantitative indicators, deriving from the linear regression analysis performed in [57] on a set of 14 redundant indices describing different facets of biomechanical motor recovery. The five indicators are briefly described in the following and are used to measure temporal, spatial, and force features of motor skill recovery.

- *Aiming angle* synthesizing features related to motion accuracy and direction. It is defined as the angular difference between target direction and the direction of travel from the starting point up to peak speed point [49, 50]. The angular displacement is expected to reduce with the therapy.
- *Length ratio* evaluating the improvement of the path length. It is formally defined as the length ratio between the actual patient curve and the desired straight line. An improvement of patient motion capabilities makes the actual path tend to the straight line and consequently makes length ratio tend to one. The length ratio provides a measure of patient ability to reach the target, by means of a threshold value of 0.5; index values under the threshold indicate patient inabilities to achieve the final point.
- *Jerk index* measuring the change of motion smoothness with recovery. It is calculated by dividing the mean jerk magnitude by the trajectory length. Note that increases in the jerk index correspond to decreases in smoothness. A decrease of this index following robot training is expected.
- *Useful force* synthesizing features related to force regulation and direction. It measures the amount of mean force directed towards the target. The useful force is calculated by weighting the mean force value

(extracted by x, y, z force components) with the aiming angle index normalized with respect to its maximum (that is 90° in our case). It ranges between zero, when the aiming angle is over 90°, and the mean force value, when the aiming angle is zero. An increase with recovery is expected.

- *Useful work* synthesizing features related to work regulation and direction. It measures the amount of total work directed towards the target and is calculated by weighting the total work value with the aiming angle index normalized with respect to its maximum (that is 90° in our case). The total work is the line integral of force over the curve described by the patient. It will vary between zero and total work. An increase with recovery is foreseen in free motion as well as in resistive motion.

2.4.2 Motion decomposition algorithm and indices related to motion planning

Acceleration data were recorded through the magneto-inertial unit. It provided global hand acceleration (including gravity) and its orientation (in terms of rotation matrix) with respect to a fixed reference frame, defined during sensor calibration. The rotation matrix allowed calculating the gravity contribution to be subtracted to the global hand acceleration. Velocity signals from the robot were synchronized with acceleration data from the magneto-inertial unit by means of a square wave trigger signal (ranging between 0 and 5 V), sent from the robot to the magneto-inertial unit.

The recorded acceleration data were twice differentiated to obtain jerk and snap signals. A Savitsky-Golay filter on a 250 ms window of acceleration data (4th order) was used for differentiation. It is a low-pass filter with cutoff frequency of 6.83 Hz [50].

Velocity signals from the robot were off-line processed in order to extract submovements composing subject overall motion. As reported in Eq. (1) and shown in Fig. 2, minimum-jerk submovements can be uniquely described by three parameters—the amplitude of the pulse signal, i.e., peak value A, the time at which the peak occurs t, and the duration of the submovement w:

$$v(\tau) = \frac{A}{1.875} \left(30 \left(\frac{\tau - t + \frac{w}{2}}{w} \right)^2 - 60 \left(\frac{\tau - t + \frac{w}{2}}{w} \right)^3 \right.$$
$$\left. + 30 \left(\frac{\tau - t + \frac{w}{2}}{w} \right)^4 \right) \quad t - \frac{w}{2} \leq \tau \leq t + \frac{w}{2}$$
$$= 0 \quad \text{otherwise} \tag{1}$$

Relying on the hypothesis delineated in Sect. 1 about the existence of a rhythmic neurocontroller, sequentially
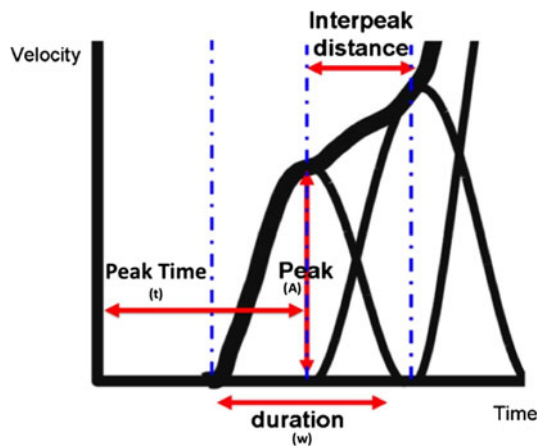
Fig. 2 Main submovement features: duration, peak value, and interpeak temporal distance (adapted from [44])

Fig. 3 One single submovement. The beginning of movement is identified by a local max in the snap (s_1), the first flex of the acceleration corresponds to a max of the jerk and a zero of the snap (j_1), and the first peak of the acceleration corresponds to a zero in the jerk and a min in the snap (a_1). The first peak in the velocity profile (v) corresponds to a zero in the acceleration, a min in the jerk, and a zero in the snap. The temporal distance from s_1 and j_1 is a constant fraction of the whole movement. (Adapted from [10])

sending to upper-limb pulse signals at a specific sample rate, duration w and peak time t were kept constant whereas amplitude A varied. This also entailed that, for each subject, the initial part of the movement, not being modified by overlapping with previous submovements, contained all the constant information about the pulse signals.

Accordingly, the approach presented in [10] based on acceleration, jerk, and snap signals was followed to identify the beginning of the bell-shaped submovements and the interpeak distance (related to peak time t), being a constant among different trials. Interpeak distance (named s_1–j_1 in Fig. 3) is the temporal distance from movement beginning and the insurgence of the second submovement, which is identified through the first inflection in the acceleration profile. Duration w of a single submovement can be calculated by multiplying the interpeak distance for the constant fraction of the analytical curve that describes the bell-shaped velocity profile (Fig. 3). Thus, the first submovement has duration w starting from the beginning of the movement, the second submovement is shifted in time of the interpeak distance and has the same duration w, and so on.

Given w and t, the amplitude of each submovement in the sequence was determined by means of the branch and bound optimization algorithm, described in detail in [43]. The optimizer finds the best velocity peak for each submovement able to minimize the difference between the recorded velocity profile and the reconstructed velocity profile given by the superposition of the identified submovements.

Subject motor behavior can be described in terms of composition strategy applied by her/him to plan and generate the arm point-to-point motion. The following indices are proposed to analyze such a strategy:
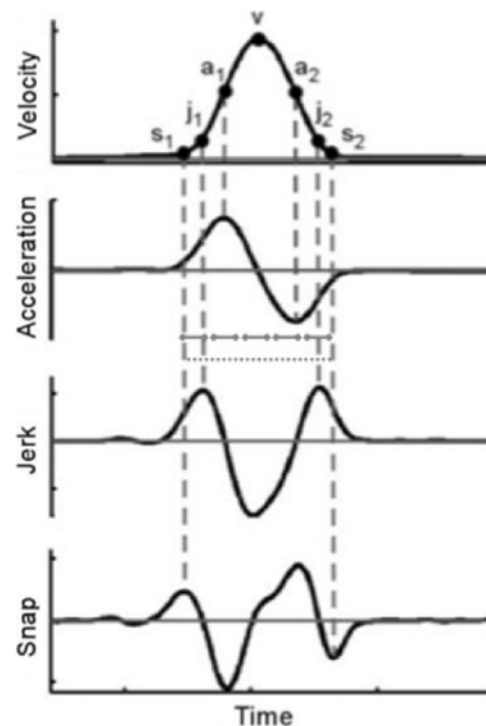
- Movement duration, later called *total duration*. It is measured by means of the execution time, defined as the time for performing a point-to-point movement, elapsed from movement onset (i.e., time instant where velocity exceeds a threshold of 10% of peak velocity [49, 50]) and movement termination (i.e., time instant where velocity goes below a threshold of 10% of peak velocity). Movement duration is expected to reduce with recovery.

- Temporal duration of each submovement w, later called *ΔT_submov*. As shown in Fig. 2 it is one of the three main features of submovements. It is highly dependent on the subject and the limb inertia. Thus, each subject is expected to have her/his own submovement duration, which increases with the inertia of the moved body district, but it is constant with the training. The experimental trials allow investigating if *ΔT_submov* is intrinsic in the patient, independently of the pathological level, or if it varies with recovery.

- Submovement frequency, called *rate_submov*. It is defined as the inverse of interpeak distance and represents the rate that the neurocontroller uses to produce motion units in sequence. Coherently with *ΔT_submov*, it is expected to keep constant with training.
- Submovement numbers, i.e., *N_submov*, that is linked to motion total duration, submovement duration and submovement frequency. They are regarded as the number of consecutive motion units to be gradually produced to reach the target. Coherently with movement duration, a reduction with training is expected.
- *Peak speed*: It is the peak value of patient velocity. An increase of peak speed is expected, being subjects required to move as fast as possible towards the target.
- *Peak time%*. It is defined as the ratio between the time instant of the peak value of the velocity profile and the total motion duration. It is expected that, contextually with the increase of velocity, a time shift of the peak speed to the middle of the motion time interval is observed, in compliance with the motion constraint of maximizing smoothness. Consequently, a value of *Peak time%* tending to 0.5 is foreseen.

2.5 Statistics

Paired Student *t* tests were used to (i) verify that the population of subjects was homogenous at admission as well as at discharge; (ii) measure the statistical significance of the change of robot-based measurements from admission to discharge.

A Wilcoxon signed-rank test was used to assess the research hypothesis that changes in body functions between admission and discharge evaluation scores would be statistically significant.

A linear regression analysis was performed with the purpose of searching for a correlation between FM and MP clinical scores and quantitative indicators. In the regression analysis, the clinical scores were taken as dependent variables and the indicators were regarded as independent variables. Pearson coefficient *R* was used to define the level of correlation.[1]

3 Results

3.1 Clinical findings

Robot-aided motor therapy led to significant reduction in motor impairment of the paretic limb from admission to

discharge. Statistically significant gains were found with the Wilcoxon test on the FM (22.26 ± 9.841 (mean $\pm$ SD) at admission and 28.83 ± 10.87 (mean $\pm$ SD) at discharge, $P < 0.0001$, $z = -4.23$) and the MP (35.00 ± 4.93 (mean $\pm$ SD) at admission and 40.22 ± 6.07 (mean $\pm$ SD) at discharge, $P < 0.0001$, $z = -4.23$) clinical scales.

3.2 Robot-based evaluation

Figure 4 reports the motion trajectories of one representative patient during a point-to-point evaluation task in pre-treatment and post-treatment phases, respectively. It is evident the improvement towards more linear trajectories over the 80 trials and, mainly, the improved capability of extending the arm towards the more distal targets, in the top of the plot.

Tables 2 and 3 report the results of robot-based evaluation during unperturbed and resistive motion, respectively. Patients globally improved kinematic and dynamic performance and all indices varied in the expected direction with statistically significant changes. In accordance with [49, 50], indices related to motion velocity and smoothness were not reported for resistive motion, being meaningless for perturbed movements. As regards dynamic performance, it can be observed that the amount of total force and total work directed towards the target (namely the useful force and the useful work) significantly increased in unperturbed as well as in perturbed motion, as a consequence of the combined improvement of motion direction and force regulation.

3.3 Correlation analysis

Tables 4 and 5 report the results of the linear regression analysis carried out to study correlation between clinical measures (i.e., FM and MP scores) and quantitative indicators, obtained by the robot data.

In the case of unperturbed motion (Table 4), *aiming angle* and *jerk index* moderately correlated with statistical significance with FM/66. *Aiming angle* correlation with MP was stronger. Finally, neither *length ratio* index nor *force* and *work* indices showed significant correlation with the clinical scores.

Table 5 reports regression statistics for the case of resistive motion. Results on kinematic indices were comparable to the case of unperturbed motion, with in general weaker correlation coefficients. The main difference with data in Table 4 is that force and work indices significantly correlated with clinical scores, being the task addressed to stimulate force control. Mainly for two indices, *aiming angle* and *useful force*, correlation with MP was high, while correlation with FM was moderate.

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[1] $0 < R \leq 0.3$ indicates a weak correlation; $0.3 < R \leq 0.7$ indicates a moderate correlation; $R > 0.7$ indicates a strong correlation [19].
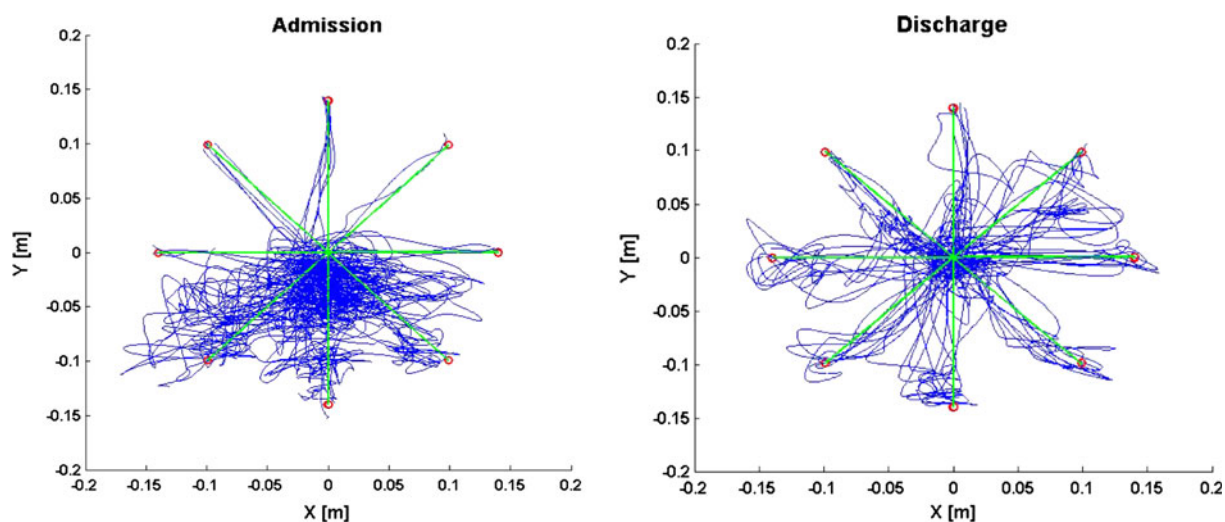
Fig. 4 Plot of 80 trials of unperturbed motion for a representative subject. The reference straight line is in *green* and actual patient motion is in *blue*. (Color figure online)

Table 2 Biomechanical indices for unperturbed motion task

Kinematic index	Admission (mean ± SD)	Discharge (mean ± SD)	t_{23}	P	R
Motion direction					
Aiming angle (°)	23.81 ± 15.92	14.24 ± 10.25	5.88	<0.001	0.73
Path length					
Length ratio	0.68 ± 0.13	0.76 ± 0.09	−3.85	<0.001	0.74
Motion smoothness					
Jerk index (1/s^3)	2.12 ± 0.19	1.96 ± 0.14	4.73	<0.001	0.75
Force exerted during motion					
Useful force (N)	1.42 ± 0.53	1.64 ± 0.52	−2.47	0.021	0.42
Work expended during motion					
Useful work (J)	0.15 ± 0.06	0.18 ± 0.06	−2.71	0.012	0.49

Table 3 Biomechanical indices for resistive motion task

Kinematic index	Admission (mean ± SD)	Discharge (mean ± SD)	t_{23}	P	R
Motion direction					
Aiming angle (°)	28.51 ± 23.81	17.29 ± 18.80	3.78	0.001	0.53
Path length					
Length ratio	0.57 ± 0.19	0.64 ± 0.13	−2.86	0.009	0.47
Force exerted during motion					
Useful force (N)	8.25 ± 4.00	10.13 ± 3.51	−2.35	0.028	0.51
Work expended during motion					
Useful work (J)	0.80 ± 0.58	1.08 ± 0.66	−2.69	0.007	0.47

3.4 Submovement-based evaluation

Figures 5 and 6 report hand trajectories and velocity profiles (recorded in red and reconstructed in blue) of a representative subject from the comparison group, and a representative stroke patient during a point-to-point evaluation task in pre-treatment and post-treatment phases, respectively. It is evident the improvement towards more symmetric bell-shaped velocity and, mainly, the improved capability to move smoothly, with less corrective submovements towards the target, in a way similar to the healthy subjects.

The reconstructed velocity profile originates from the composition of sequences of submovements. The fitting

Table 4 Correlation between robot-based indicators and clinical scores for unperturbed motion

Performance index	FM/66		MP	
	R (Pearson coefficient)	P (<0.05)	R (Pearson coefficient)	P (<0.05)
Movement direction				
Aiming angle (°)	0.69	0.0002	0.79	<0.001
Path length				
Length ratio	0.34	0.1	0.53	0.008
Motion smoothness				
Jerk index ($1/s^3$)	−0.53	0.008	−0.49	0.014
Force exerted during motion				
Useful force (N)	−0.12	0.58	0.24	0.26
Work expended during motion				
Useful work (J)	−0.11	0.60	0.26	0.21

Table 5 Correlation between robot-based indicators and clinical scores for resistive motion

Performance index	FM/66		MP	
	R (Pearson coefficient)	P (<0.05)	R (Pearson coefficient)	P (<0.05)
Movement direction				
Aiming angle (°)	−0.57	0.005	−0.72	<0.001
Path length				
Length ratio	0.37	0.08	0.49	0.02
Force exerted during motion				
Useful force (N)	0.49	0.017	0.77	<0.001
Work expended during motion				
Useful work (J)	0.57	0.005	0.58	0.004

Fig. 5 Hand trajectory and velocity profile for one representative healthy subject (recorded velocity is in *red*, reconstructed velocity is in *blue*). The resultant vector of hand position and velocity is reported over time. (Color figure online)
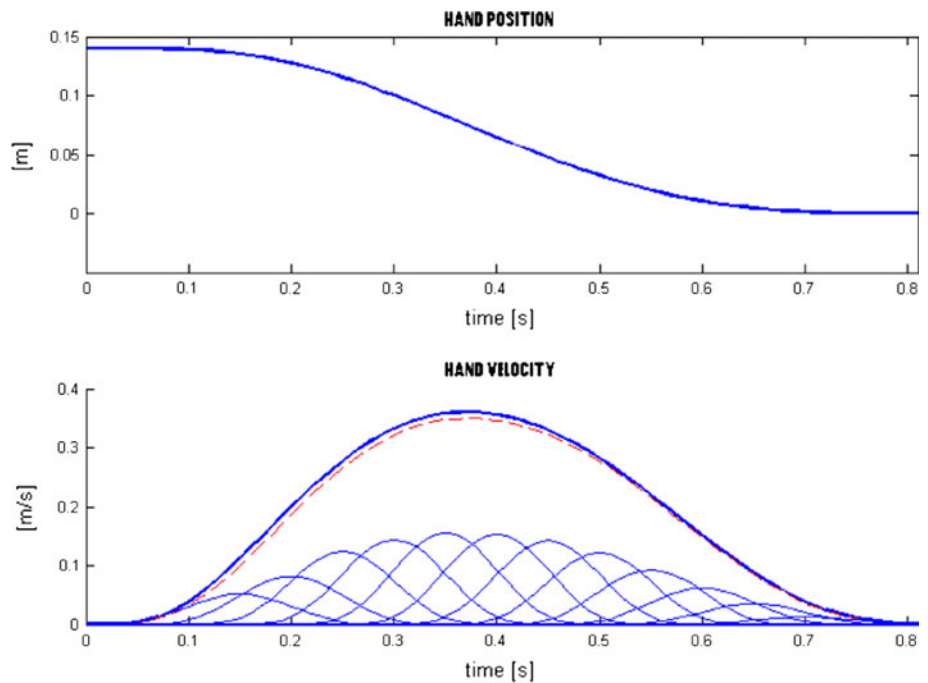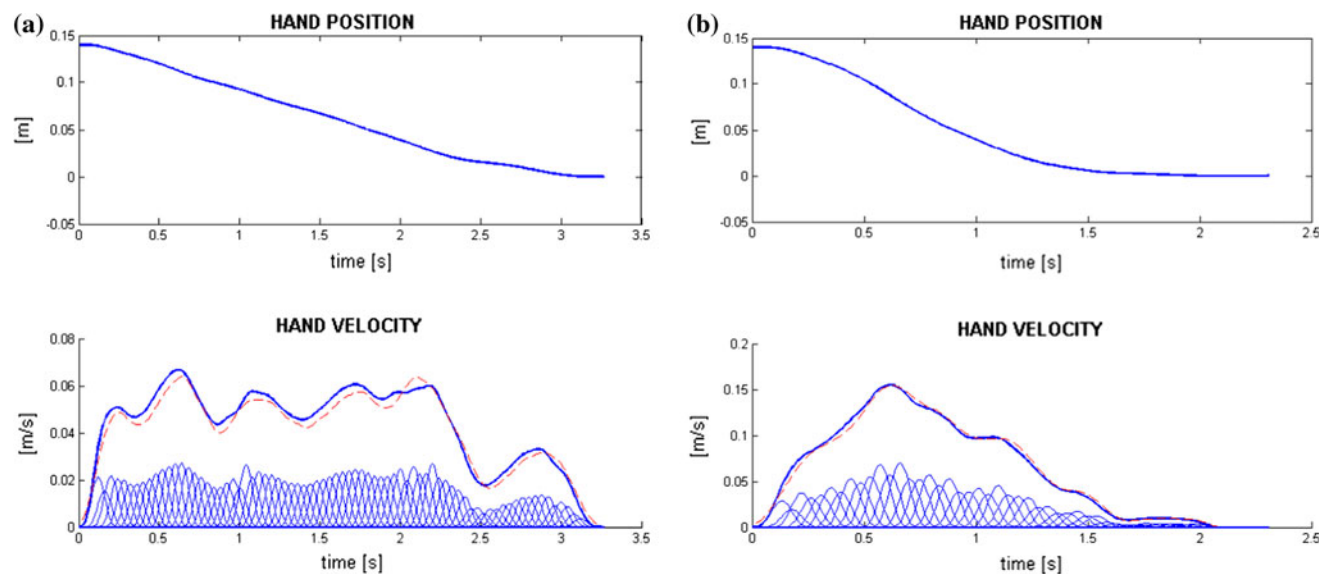
Fig. 6 Hand trajectory and reconstructed velocity profile (in *blue*) for one representative stroke patient at admission (**a**) and discharge (**b**). In *red* the recorded velocity profile is shown. (Color figure online)

error, i.e., the mean squared error between recorded and reconstructed velocity profiles, is 1.43e−4 m/s.

Table 6 reports submovement features for the comparison group, whereas Table 7 shows the same features for five stroke patients. Future analysis on a wider number of subjects will be carried out to study intra-subject and inter-subject variability. Although considering that data on stroke subjects are very preliminary due to the poor number of subjects, the following features can be observed:

– A quite constant value for submovement duration and rate, thus confirming the hypothesized subject-specific features;
– A progressive reduction of motion total duration accompanied by a reduction of submovement number, which tend to the average value observed in the comparison group (i.e., 883 ms and 15 submovements);
– An increase of peak speed, as a result of training;
– A shift of the velocity peak to the center of the time interval, thus tending to approximate a symmetric bell-shaped velocity profile. This is perfectly aligned with

the optimization minimum-jerk strategy of maximizing smoothness.

4 Discussion

Clinical evidence in physical medicine and rehabilitation clearly demonstrates that there is an important and increasing demand for innovative therapeutic solutions to address a wide variety of pathologies; for instance, patients experiencing severe stroke events have a high probability, in most cases higher than 50%, to retain severe disabilities for the rest of their lives. The positive correlation of the prevalence of many neuromotor diseases with age can give a good idea of the social relevance of this research area. Many industrialized societies predict that in the near future 20–35% of their population will be over the age of 65 and in need of rehabilitation support.

Robotics can greatly contribute to physical medicine and rehabilitation from a twofold perspective: assisting therapy

Table 6 Submovement-related performance indices in healthy subjects

Subject no.	ΔT_submov (ms) (mean ± SD)	Rate_submov (Hz) (mean ± SD)	Total duration (ms) (mean ± SD)	N_submov (mean ± SD)	Peak speed (m/s) (mean ± SD)	Peak_time% (mean ± SD)
1	290 ± 42	20.83 ± 4.17	775 ± 95.74	15 ± 2	0.39 ± 0.03	0.49 ± 0.05
2	285 ± 60	21.03 ± 4.20	725 ± 28.87	12 ± 1	0.34 ± 0.02	0.58 ± 0.04
3	255 ± 60	23.25 ± 6.95	1153 ± 49.24	23 ± 3	0.24 ± 0.01	0.42 ± 0.03
4	240 ± 25	25.01 ± 6.74	950 ± 57.74	20 ± 3	0.29 ± 0.09	0.46 ± 0.10
5	300 ± 48	20.1 ± 4.19	813 ± 47.87	13 ± 2	0.40 ± 0.07	0.47 ± 0.02

Table 7 Submovement-related performance indices in stroke subjects

	FM/66	MP Adm	ΔT_submov (ms)	Rate_submov (Hz)	Total duration (ms)	N_submov	Peak speed (m/s)	Peak_time%
Subject 1								
Admission	20	38	240 ± 48	25 ± 4.3	3250 ± 108	77 ± 1	0.09 ± 0.02	0.14 ± 0.06
Discharge	25	43	260 ± 66	23 ± 4.7	2200 ± 283	48 ± 7	0.17 ± 0.013	0.29 ± 0.029
Subject 2								
Admission	29	43	250 ± 54	25 ± 6.7	1575 ± 189	31 ± 2	0.22 ± 0.013	0.30 ± 0.062
Discharge	35	50	240 ± 42	25 ± 3.9	1025 ± 126	23 ± 3	0.29 ± 0.046	0.43 ± 0.044
Subject 3								
Admission	10	23	240 ± 42	25 ± 2.9	1975 ± 238	53 ± 2	0.15 ± 0.029	0.40 ± 0.065
Discharge	19	27	220 ± 36	28 ± 2.8	1507 ± 92.9	41 ± 3	0.20 ± 0.026	0.52 ± 0.058
Subject 4								
Admission	27	41	300 ± 48	20 ± 4.2	1485 ± 38.7	27 ± 4	0.21 ± 0.022	0.33 ± 0.022
Discharge	34	46	260 ± 78	23 ± 3.9	765 ± 46.5	16 ± 2	0.35 ± 0.023	0.46 ± 0.021
Subject 5								
Admission	33	43	280 ± 42	23 ± 3.9	1525 ± 125	30 ± 3	0.22 ± 0.046	0.33 ± 0.044
Discharge	39	47	300 ± 48	20 ± 4.2	925 ± 38.9	15 ± 2	0.30 ± 0.022	0.51 ± 0.008

administration and providing objective patient assessment. However, nevertheless therapy is performed through robotic machines, body functions, and structures assessment is typically carried out by means of traditional clinical impairment scales [31], which can suffer from being subjective, operator-dependent, qualitative. On the other hand, robots can measure position and force with high accuracy and frequency [5]. In this perspective, the robot sensory system (possibly in addition to other sources of information) plays a fundamental role. Data from the patient (such as kinematic, dynamic and physiological data) could be processed for a continuous analysis of her/his motion intentions and physiological state. These information could be used to (1) online update robot control during the execution of a motor exercise in order to guide, help or force the patient limb toward the target in accordance to his/her residual motion capabilities; (2) apply corrective actions in case of incorrect motion; (3) provide therapists with objective, accurate measurements of subject's body functions, thus enabling therapists to track subject progress in therapy, evaluate the efficacy of various interventions and customize the machine for each particular user.

This paper presents a preliminary study of quantitative assessment of biomechanical and planning functions of stroke patients treated with upper-limb robot-aided motor therapy. A clinical study on 24 chronic post-stroke patients was carried out. The InMotion2 and InMotion3 robotic machines were used to deliver therapy. A double evaluation of subject motor performance following robotic training was carried out. The first one was based on traditional clinical impairment scales, in order to assess short-term changes in chronic stroke patients and compare them with the literature. The second one consisted of biomechanical analysis of motor functions, grounded on robot-based kinematic and dynamic evaluation during unperturbed and perturbed point-to-point motion, and analysis of planning functions, based on acceleration data from a magneto-inertial sensor and submovement identification. The analysis of planning functions relies on our preliminary studies on the existence of a neural controller, embedded in the brain, that is discrete, works rhythmically, and sequentially sends pulse signals (i.e., submovements) at a specific sample rate to each limb segment [46, 56].

The concept of *discrete neural controller* is not new in the literature. Most models of neuro-controllers responsible for controlling upper-limb movements with signal-dependent neuromuscular noise are grounded on the concept of "discrete controller", intermittently sending discrete corrections [1, 10, 12, 30, 36, 37, 39, 40, 55]. This theory is still controversial and a number of works state that submovements are actually the result of a single continuous neuro-controller [2, 21, 48]. However, it is quite implausible that a continuous control mechanism could produce velocity profiles that can be decomposed in sub-elements all equally shaped. Moreover, it is worth observing that a continuous control process should predict a relatively fixed correction latency, which is determined by the sensorimotor delay [47]. As recently demonstrated in monkeys by Fishback et al. [10, 11] there is not such fixed correction latency, but rather a wide range of correction latencies. The data reported in the literature so far seem to be more consistent with a mechanism of intermittent control rather than with a continuous control process.

On the other hand, as regards the generation of pulse signals with specific sample rate, it can be observed in the experimental trials reported in a number of studies [10, 30, 54] that submovements appear to be characterized by constant behavior in terms of duration, frequency, and mutual overlapping and a properly optimized scaling of amplitude and number. Accordingly, for each subject, the pulse signals are supposed to have the same shape (i.e., "bell-shaped" velocity commands [38]), duration and mutual overlapping, and differ in their velocity peak value. Moreover, these bell-shaped velocity profiles can be analytically expressed through three parameters, i.e., duration, overlapping, and peak value, in order to satisfy the minimum-jerk constraint [1, 12, 30].

The study of the mechanisms involved in motor planning and control in chronic stroke through the analysis of the change of submovement features is new in the literature. Consequently, it required carrying out a preliminary analysis on a comparison group, which is reported in this paper.

Globally, the results of this study reinforced earlier findings that short-term, goal-directed robotic therapy could significantly improve functions and structures of the exercised limb segments in persons with chronic stroke [5, 42, 52]. An average increase of FM scores by 9.9% and MP scores by 7.4% from admission to discharge were elicited.

Biomechanical assessment of motor functions was carried out through a core set of five performance indicators extracted in a pilot study in [57] over a set of fourteen redundant biomechanical indices, by means of a multivariate regression analysis. They resulted to be the minimum set of indices able to quantitatively describe facets of motor recovery related to kinematic and dynamic changes in chronic stroke patients. In this paper they are further investigated and validated on a larger number of patients, thus contributing to enforce their validity and statistical significance.

The analysis of biomechanical data in unperturbed and perturbed tasks of reaching (Tables 2, 3) showed that all the performance indicators changed in the expected direction. It can be regarded as a result of the re-learning process, which improved subject capabilities of moving and coordinating the degrees of freedom of the upper limb, with main effect on elbow extension. As regards force and work indices, as expected, higher changes were obtained in the resistive tasks; however, their variation was always significant, being the result of two components, one dynamic (i.e., force) and the latter kinematic (i.e., direction). It is worth noticing that useful force variation, which resulted slightly above the significance threshold in [57], are now widely significant because of the increased number of subjects. The choice of using useful force and useful work (instead of pure force or work) as significant indices

for describing dynamic features was due to the type of robotic training consisting of assisted kinematic-goal-directed exercises, which stimulated the improvement of motion kinematics more than force control. In fact, given the evidence in the literature on patient behavior prone to manage many independent elements in reaching movements by means of compensatory actions [6, 29, 51], we supposed that, when the patient was required to reach only kinematic targets, she/he also applied compensatory strategies which avoided him/her to control other independent elements, such as force.

The linear regression analysis between FM and MP scores and performance indices showed that the two clinical scales correlated with the same indices, even if moderately in most cases. Correlation was weak for useful force and useful work calculated for unperturbed motion. The achieved results confirmed and enforced our preliminary findings in [57]. Correlation with MP was generally stronger than correlation with FM. This difference accentuated in the resistive motion task. Pearson coefficients between force and work variables and MP scores ranged between 0.58 and 0.77 (Table 5). Correlation with FM measures was still present but it was moderate. In addition, it is worth observing in Table 4 that correlation coefficients with path length index (i.e., length ratio) and smoothness index (i.e., jerk index) were very low for both clinical scales. This demonstrates that neither FM nor MP accounts for performance related to motion velocity and path length, and weakly accounts for motion features related to smoothness.

The analysis of features involved in motor planning pointed out important results, even if preliminary. Firstly, all the results were consistent with the theory on the existence of a discrete neuro-controller rhythmically producing bell-shaped velocity pulses during motion planning. The analysis on the comparison group (Table 6) showed that for each subject, constant values of submovement duration and frequency can be identified and that they can be regarded as subject invariances.

On the other hand, modifications in planning strategies can be only related to changes in submovement amplitude, number and order. Similar results were observed in the five stroke patients (Table 7). They were able to plan upper-limb motion as sequences of submovements with constant duration and frequency at the pre-treatment as well as the post-treatment phases. However, for a given task, the planning strategy modified with training in terms of number of submovements, order and corresponding amplitude, and time of application of the peak speed, by tending to approximate the behavior observed in the age-matched healthy subjects. For instance, from admission to discharge, for patient 1 the number of submovements reduced of 29, motion duration decreased of 1050 ms, peak speed

increased of 0.08 m/s and peak time changed of 15%; on the other hand, for patient 2 the number of submovements reduced of 9, motion duration decreased of 550 ms, peak speed increased of 0.07 m/s, and peak time changed of 13%. It is also worth noticing that the two patients had two different levels of disability, being patient 1 more severe than patient 2. Correspondingly, submovement features of patient 2 were closer to healthy subjects than the other one.

From the literature it can be observed that, in healthy subjects, slower movements aimed to higher accuracy are characterized by more submovements than faster movements, as an indirect measure of the major involvement of feedback control with respect to feedforward. On the other hand, this study shows that in stroke patients slow movements are conditioned by their reduced motor capabilities more than by the search for accuracy. Therefore, slow movements have more submovements and lower accuracy than faster movements. The number of submovements can still be regarded as an indirect measure of a continuous feedback control action, which tries to apply long sequences of corrective actions to reach the target. However, along with recovery, motor capabilities for a given task improves together with the efficiency of the feedback control, thus resulting in the reduction of total motion duration and, contextually, in the reduction of the number of submovements with an increase of the accuracy.

This study was limited to proximal upper-limb evaluation of a chronic stroke population and to a very preliminary analysis of the modification of patient planning and control strategy over training. However, it lies the foundations for important studies on patient motor control and provides a set of indices related to biomechanical and planning facets of motor recovery potentially applicable to other body districts, and to acute and subacute stroke population as well as to other pathologies. Thus, relying on the preliminary achieved results, future efforts will be addressed to (i) provide a clinical interpretation of the defined set of indices; (ii) extend the study on submovement composition strategy to a higher number of patients, in order to provide a statistical evidence of the achieved results; (iii) extend the study to distal upper-limb districts, starting from the same set of 24 patients already trained with the InMotion3 robotic machine; (iv) correlate acceleration data with EMG signals for retrieving the origin of submovements in the muscular activity; (v) further investigate basic mechanisms of sensory-motor recovery, in combination with brain imaging technologies.

In conclusion, a preliminary study of multimodal analysis of human functions undergoing upper-limb robot-aided therapy was presented in this paper. The two major contributions provided by this study consist of (i) analyzing upper-limb biomechanical features by means of a novel core set of robot-based indices assessing kinematic and dynamic performance; (ii) studying motor planning functions by means of submovement decomposition algorithms. The use of performance indicators grounded on submovement features is completely new in the literature and provides promising insights into recovery assessment of both motor planning functions and control in stroke patients.

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