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Important Parameters for Hand Function Assessment of Stroke Patients

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Abstract

Clinical scales such as Fugl-Meyer Assessment and Motor Assessment Scale are widely used to evaluate stroke patient's motor performance. However, the scoring systems of these assessments provide only rough estimation, making it difficult to objectively quantify impairment and disability or even rehabilitation progress throughout their rehabilitation period. In contrast, robot-based assessments are objective, repeatable, and could potentially reduce the assessment time. However, robot-based assessment scales are not as well established as conventional assessment scale and the correlation to conventional assessment scale is unclear. This paper discusses the important parameters in order to assess the hand function of stroke patients. This knowledge will provide a contribution to the development of a new robot-based assessment device effectively by including the important parameters in the device. The important parameters were included in development of iRest and yielded promising results that illustrate the potential of the important parameters in assessing the hand function of stroke patients.

Keywords: motor assessment scale, rehabilitation, robotic, stroke, assessment

1. Introduction

The use of robotic devices for physical rehabilitation of the upper limb following brain injury can assist physiotherapists in rehabilitation program [1]. In addition, the use of these devices will lead to similar or larger improvements of motor function than conventional therapy [2,3]. These devices can increase the intensity of the training beyond what is currently possible [4], as well as repetitive [5], systematically [6] and encourage motivation through game-like virtual reality technology [7-9] with minimal supervision [10]. Besides, robotic devices can measure the patient's sensory-motor performance precisely and objectively by integrating sensors [11]. Such data could be used to redefine the rehabilitation strategy or even reconstruct the clinical score [4,12]. Moreover, robotic measure can also provide immediate feedback on patient's progress and would reduce the subjectivity inherent in most of the conventional assessment scales [13].

An added benefit of robotic rehabilitation devices is that the built-in technology can accurately measure kinematic information such as position, velocity and force about the user's movements as they undergo robotic training. Conversely, conventional assessment scale is limited by subjective observation of the therapist and patient. There are two potential benefits if kinematic information could be converted into clinical meaningful information [14]: i) The quantitative measurement of patient's performance allows more effective rehabilitation program to be customized. The rehabilitation will be data-driven and training parameters tuned to ensure the meaningful training, ii) Automated and quantitative functional assessments would reduce the subjectivity inherent in many of the conventional assessment scales.

2. Mechatronic Approach

The main objective of this paper is to cater to a wide audience regarding the hand function assessment tool for stroke patients in rehabilitation application. The information

collected from various works around the world will be very useful for researchers who require a wide overview on stroke quantitative assessment device. In addition, the review of the important parameter require for the effective design of the device should provide an excellent starting point for researchers who are looking for a one-stop reference that provides good fundamental knowledge to jump-start their own research. To complement all these, a meticulous list of references is provided for those interested in probing the issues raised in this paper further. Finally, a new approach to assess the hand function of stroke patients is also explained in this paper.

A number of studies have examined the relationship between the kinematic variables measured by robots (including completing time, smoothness, speed accuracy and force produced) and the conventional assessment scales used for stroke survivors. Several studies [3,12,15-18] tested the performance of the extracted kinematics variables from MIT-Manus, HapticKnob, ArmeoSpring, IE2000 haptic joystick, wrist/shoulder-elbow device and NJIT RAVR system to predict the several clinical score such as FMA, Motor Status Score (MSS) and Motor Power scale (MP). The tasks were basically the subject need to perform robotic assessment unconstraint or resistive movements dependent on the device with game like virtual reality environment.

Besides robotic assessment, some research used motion capture to assess the performance of hand function of stroke patients. For example, Murphy *et. al.* [19] recorded the movement trajectories of stroke patients during drinking from a glass task and Chang *et. al* [20] asked the stoke patients to perform the reaching forward task with their affected limb as fast as possible where the paper cup as a target by using a motion capture system.

Wearable sensors also could address the limitation of conventional assessment scale [21-23]. Wearable sensors could be used as quantitative assessment tools or as an addition to observational clinical tools. Sensors such as accelerometer and inertia sensor have the ability to capture specific patterns of movement relating to motor disabilities. Furthermore, this system allows voluntary movements of the subject without assistance from others. Previous studies showed that the kinematic variables extracted from the wearable sensors can be used to predict the conventional assessment scale score in the stroke populations [24-26]. Subjects were asked to perform several tasks such as drinking, placing the hand from lap to a table, push and pull a weight across a table, lifting a pencil, flipping a card, turning a key and etc. The recorded kinematics data was then analysed and correlated with the clinical scale scores using linear regression techniques. Table 1 shows the summary of the mechatronics approach for quantitative assessment of the hand function.

Table 1. Summary of Mechatronics Approach for Upper Limb Assessment

Device	Movement	Strategy	Clinical Scale	Correlation	Limitation
MIT-Manus	Shoulder and elbow	Unconstrained movements with Virtual reality environment	FMA MSS MP	$R = 0.40$ $R = 0.59$ $R = 0.53$	Hand manipulation movement was excluded
HapticKnob	Forearm rotation and Hand opening/closing	Resistive movements with virtual reality environment	FMA MI MAS MoAS	$R = 0.67$ $R = 0.69$ $R = 0.60$ $R = 0.79$	Reaching movement was excluded
Armeo Spring	Whole upper limb	Unconstrained movements with Virtual reality environment	GRASSP ARAT SCIM	Adjusted $R^2 = 0.78$ Adjusted $R^2 = 0.73$ Adjusted $R^2 = 0.77$	Attach/detach and tune the parameter to adapt the user hand are time consume
IE2000 haptic joystick	Wrist and forearm rotation	Unconstrained movements with Virtual reality environment	FMA ARAT JT MAL	$R \le 0.74$ $R \le 0.83$ $R \le 0.63$ $R \le 0.57$	Reaching and hand opening/closing movement was excluded
Wrist and shoulder-elbow device	Shoulder, elbow and wrist	Resistive movements with virtual reality environment	FMA MP MSS	$R \le 0.55$ N/A N/A	Hand manipulation movement was excluded
NJIT RAVR	Whole upper limb	Unconstrained movements with Virtual reality environment	JTHF	adjusted $R^2 \le 0.56$	Complex tasks

Table 1. Summary of Mechatronics Approach for Upper Limb Assessment

Device	Movement	Strategy	Clinical Scale	Correlation	Limitation
Motion capture	Whole upper limb	Voluntary movements with real environment	FMA ARAT MoAS	$R \leq 0.53$ $R \leq 0.81$ $R \leq 0.04$	Attach/detach markers is time consuming.
Wearable sensors	Whole upper limb	Voluntary movements with real environment	FMA MAS WMFT CM FAS	$R \leq 0.53$ $R \leq 0.40$ N/A N/A N/A	Attach/detach sensors is time consuming.

Abbreviation: FMA, Fugl-Meyer Assessment; MSS, Motor Status Score; MoAS, Modified Ashworth Scale; MI, Motricity Index; MAS, Motor Assessment Scale; GRASSP, Graded and Redefined Assessment of Strength, Sensibility and Prehension; ARAT, Action Research Arm Test; SCIM, Spinal Cord Independence Measure; WMFT, Wolf Motor Function Test; CM, Chedoke McMaster; FAS, Functional Ability Scale.

3. Main Issues to Discuss

A number of moderate to high and statistically significant correlation have been identified between the kinematic variables and conventional assessment scale score. Although researchers have found the strong correlation between the kinematic variable scores and clinical score, it remains unclear how robotic technology is related to conventional assessment scales for measuring outcome [15,27].

In order to train and assess the functional movement that involves upper limb function principle, generally a robotic rehabilitation system with a large number of degree of freedom (DOF) is needed. Such robotic rehabilitation systems are often large and complex, requiring technical assistance and making them unsuited for decentralized use at hospitals, rehabilitation centres or homes. Generally, the more complex the mechanical design, the more expensive, less safe and less number of potential users it has [28]. However, these robotic rehabilitation systems are valuable for assessment purposes where the user's upper limb is exposed to large workspace including reaching and hand manipulation movements.

In neuroscience studies, human generally use regular motion patterns involving fewer DOF or synergies [29] to simplify motion control. Motor synergies in humans involve the natural selection of muscles and joints and their coordinated movements in order to move as a single functional unit to perform a task. Thus, it may be possible to use these motion invariance to simplify the design of dedicated rehabilitation devices that can be used for both training and assessment. For example, in reaching movements, the hand follows approximately a straight line path from the start point to the target [30] and predominantly confined to the sagittal plane [29]. ARM Guide and ReachMAN have an active DOF for reaching movement, which simplifies the design considerably and makes the device safer and cheaper relative to an exoskeleton system with 6 DOF.

Other dedicated robot that has simplified mechanism such as MIT-Manus, HapticKnob and HWARD could only perform either reaching or manipulation separately and this form of training may not transfer well to functional tasks. In addition, the missing DOF will affect the prediction of the clinical scores where the assessment process covered the whole upper limb functions. Thus, the basic movement of the upper limb (reaching and hand manipulation) must be included in the robotic rehabilitation training and assessment process. Besides, the motion capture's marker and wearable sensors are portable and would be more suitable for quantitative assessment purposes where the user's upper limb is exposed to the large workspace. However, the process of attaching and detaching the marker and the sensors together with calibration process is time consuming, probably similar or even longer than time taken using conventional method.

By using the motion capture system and wearable sensors, voluntary movement can be performed by the subjects without active intervening assistive or resistive force. Therefore, the data collected during the assessment process were recorded from the voluntary movement afforded by the subjects themselves. Good correlation between clinical scores and extracted kinematic variables of these systems have been found. During the assessment process using the robotic system, the unassisted modes were used where no force was generated by the device, and the movement was solely determined by the movement of the patient. However, the actuator from the robotic device should be back-driveable or has good control algorithm to allow voluntary movements performed by the subject. Celik *et. al* [17] reported that an unactuated

rehabilitation devices or affordable motion capture systems can provide an inexpensive and practical way of conducting clinically correlated assessments. With this in mind, a non-motorized device can be implemented to represent the subject's free movement with no external interference. Despite the absence of actuation, movements of the subjects can still be accurately sampled and recorded. On the other hand, the non-motorized system would be able to increase the safety of the device during user interaction and also reduces the development cost. Therefore, it would be beneficial if a simple, non-motorized system with few DOF can be designed to assess the upper limb function that involves reaching and hand manipulation movements as efficiently as existing complex robotic devices.

Several strategies have been used to assess the upper limb function. However, most of the strategies were used to assess the motor function by moving their upper limb to the target position without a clear guide on the computer screen. These strategies are strongly associated with proprioception or the ability to sense the position of the body in time and space [31]. Stroke patients usually depend on visual function when they move part of their body for example, during eating and walking because they have impaired proprioception [32,33]. Tasks should have a clear guidance path so that the subject understands easily what they should do. In previous studies, subjects were expected to move along in a straight trajectory from start to end positions, but the visual guidance of the desired path was not displayed. Performance was based on deviation value from the desired straight line [17]. With the presence of the guidance path or customized desired trajectory, the deviation can be calculated based on the customized path. However, the correlation between the clinical score and kinematic variable using this concept required further study.

4. Proposed Method

For the quantitative assessment method, kinematic movement analysis can provide more specific information on movement components and strategies. Although this method requires special equipment and training, it is most applicable in a research setting [19,27]. Kinematics describes the movements of the body through space and time, including linear and angular displacements, velocity, and acceleration, but without reference to the forces involved [27,34]. Therefore, the wearable sensors and imaging techniques which allow voluntary movement of the upper limb can be used to provide the quantitative assessment. By combining the robotic design concept, motion capture system and wearable sensor concept, a non-motorized system which allows voluntary movement can be developed as a tool to quantitatively assess the hand function of the stroke patients.

4.1. Hardware

A robot prototype was developed namely as iRest based on human biomechanics requirements and tested on both healthy and post stroke subjects. Next, improvements on the prototype were made based on their feedbacks and feedbacks from therapists. Figure 1 shows the iRest with the adjustable lightweight platform and the anti-slip mat. The subjects can rest their arm on the arm support to prevent excessive movement of the shoulder. Three movement mechanisms were developed, which were grasping mechanism for hand opening/closing movements, hand rotation mechanism for forearm pronation/supination and reaching mechanism for linear reaching movement as shown in Figure 1(b). The monitor provided visual feedback and the laptop was used as the host computer to communicate with iRest.

The grasping mechanism was developed based on the functional position of the hand and allowed hand opening and closing movements up to 200 mm. Two potentiometers were being used instead of one to ensure design symmetry with a balanced weight at both ends. However, only one potentiometer with a resolution of 1.25 mm was used as the position tracker of the moving fixture. The moving fixture was the part where the four fingers were placed while the thumb was placed on a static fixture, as shown in Figure 1(b). A Velcro band was included to secure the user's hand from slipping out from the handle.
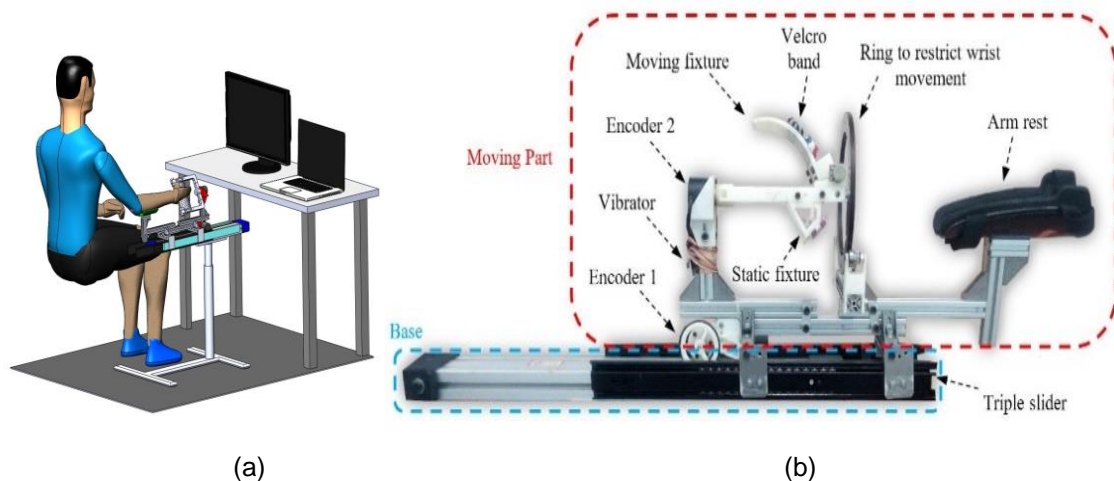
Figure 1. (a) CAD drawing of the iRest on an adjustable lightweight platform and
(b) Parts of iRest

The hand rotation mechanism of the iRest was for forearm pronation and supination movements. The design concept for hand rotation mechanism was based on Haptic Knob [6] and ReachMAN [35] robots. The grasping mechanism is directly attached to the digital rotary encoder (Encoder 2) to allow rotation of forearm in both directions (pronation and supination) for 360° while subject's hand was holding the handle. All the mechanisms can be used for both hands by rotating the grasping mechanism to the neutral position of the selected hand.

The reaching mechanism of the iRest is to generate linear reaching movement. As the reaching of the hand movement typically follows a straight line from initial to the target position [29], the design idea for this movement is to use a mechanism with only one linear axis. To avoid shoulder movement that can cause pain in some of the stroke patients [36], the linear reaching movement of iRest was limited at 236 mm with a mechanical stopper.

4.2. Software

Several robotic assessment modules were developed before deciding on the final version. All modules were implemented to simulate the movement of upper limb during conventional assessment process. In the conventional methods, isolated movements, linear combination of reaching and hand manipulation and non-linear combination of movements are assessed.

Three simplified robotic assessment modules were developed as illustrated in Figure 2, namely Draw I, Draw Diamond and Draw Circle. These modules were developed as an assessment strategy in order to assess the subject's upper limb function while playing an interactive game. As discussed in Section III, the stroke patients with impaired proprioception depended on the visual function to perform the given task. Therefore, a predefined path was developed in these modules to guide the stroke patients to perform the hand movement. With the presence of the predefined path, the trajectory to the desired target position can be customized and the deviation can be calculated based on the path.

The Draw I module was isolated into reaching and hand manipulation, but for the Draw Diamond and Draw Circle modules combine both reaching and hand manipulation movements. The red dot was the target position while the green dot represented the movement of the iRest handle. For the up and down movements of the green dot, it represented the forward and backward reaching movement of the iRest respectively. For right and left movements of the green dot, it represented the rotation of hand; clockwise (CW) rotation for right movement and counter-clockwise (CCW) rotation for left movement. The diameter of the green dot increases when the moving fixture of the handle moves away from the static fixture. Our previous studies discussed details development of these robotic assessment modules [37-39].

(a)   (b)   (c)
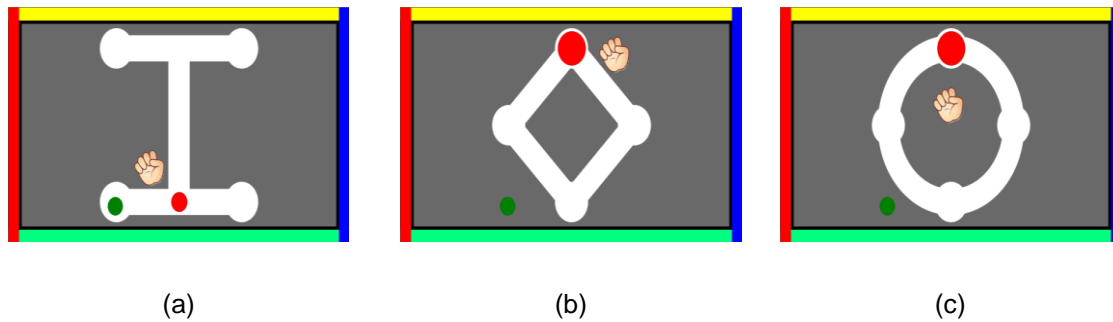
Figure 2. Robotic Assessment Module. (a) Draw I, (b) Draw Diamond and (c) Draw Circle

There are evidences which showed that elbow extension angle affects the ROM of hand rotation which are forearm pronation and supination [40]. Besides, the results showed no significant difference between ROM and velocity during performing forearm pronation and supination at two elbow extension angle 135° and 90°. Based on consultation with physiotherapists, to address this effect, the ROM of the target position for all robotic assessment modules was limited to 90° (45° pronation, 45° supination) for elbow flexion angle from 90° to 135° (0 – 150 mm). Moreover, the elbow angle changes during the reaching movement with iRest, therefore, the ROM of this movement in the robotic assessment modules was limited to 150 mm which allows the elbow to extend up to 135°. In addition, based on the hand movement section in Motor Assessment Scale (MAS) score sheet, subjects were required to pick up a polystyrene cup which has a diameter of approximately 60 mm from the table and put it on the table across the other side of their body. The ROM for hand opening task was set at 60 mm (perpendicular distance between thumbs to moving fixture of the grasping mechanism). The tolerances were set to ±3 mm for reaching, ±2° for forearm pronation/supination task and ±2 mm for grasping task. All the modules were performed similarly, where the subject had to move the handle to a target position within time allowance (Draw I, 10s; Draw Diamond and Draw Circle, 20s) and stays at the position for 0.5 seconds for a new target position to be appeared. If the subject failed to reach the target within the time allowance, new target would appear. Figure 3 shows the hand paths covered by a healthy subject and four stroke patients, the data is not discussed in this paper.
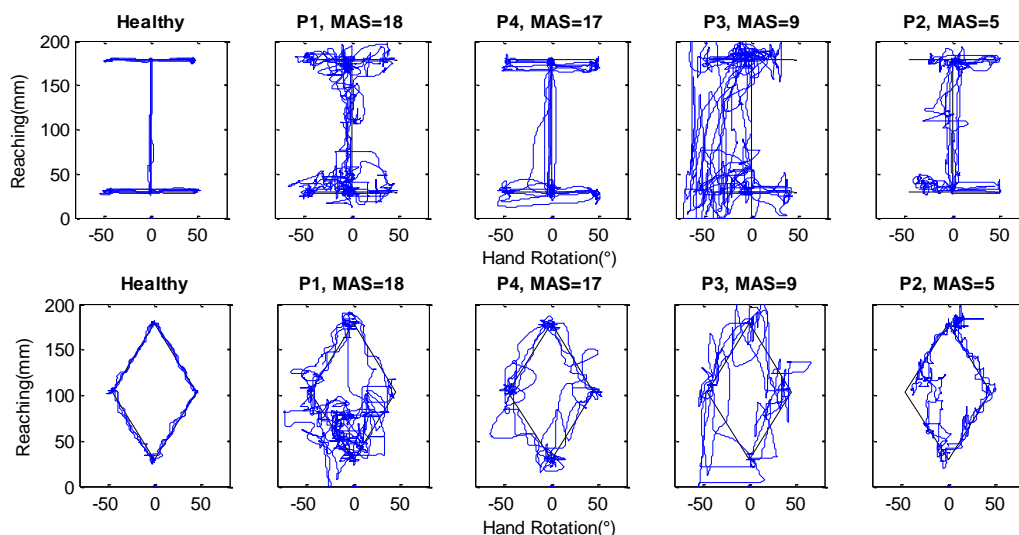

Figure 3. Hand paths covered by a healthy subject and four stroke patients (Healthy, P1, P2, P3 and P4) with different MAS, for the three robotic assessment modules
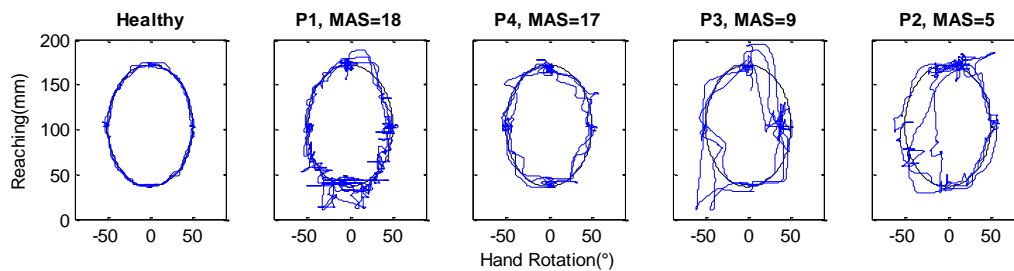
Figure 3. Hand paths covered by a healthy subject and four stroke patients (Healthy, P1, P2, P3 and P4) with different MAS, for the three robotic assessment modules

5. Performance

Fourteen stroke patients with MAS score for upper arm function section at least 3 participated in our studied. The data will be recorded once the game started. Position, time, and number of success target reach will be recorded. Several kinematic variables such as Movement Time (MT), Reaction Time (RT), Stability Time (ST), Mean Velocity (MV), Peak Velocity (PV), Time to PV (TPV), Hit Wall Score (HWS) when the green dot go beyond the white path, Path Ratio (PR), Trajectory Error (TE), Target Reached (TR), Grasping Range of motion and Smoothness were extracted from the recorded data. Our previous study explain in details about the kinematic variables [37].

The extracted data were analysed using multiple linear regression method. Zariffa *et. al.* [14] suggests four kinematic variables were high enough to produce a regression model with good performance. Therefore the best four combination of the kinematic variables were selected using leave one out cross validation (LOOCV). The combination that produced the minimum root mean square error of LOOCV ($RMSE_{cv}$) was selected using an exhaustive search of all possible combinations. Then, holdout validation method was used to split the data into training and validation data sets. Least squares error multiple linear regression models was computed for each robotic assessment module outcome using the 4 variables selected in the LOOCV process, and the training data set from the holdout validation method. Then, a model was generated for each robotic assessment module and the prediction quality for each model was evaluated using the following metrics: (i) The value of the Pearson's linear correlation coefficient or correlation coefficient, *R*. This value is a dimensionless index that measures the degrees to two variables that vary together in a range between -1 and +1 [41] and (ii) the value of root mean square error of training ($RMSE_t$) and root mean square error of validation ($RMSE_v$) of training and validation data sets were computed to investigate the predictive ability models. Table 2 shows the four combinations of the kinematic variables in predicting the MAS score during LOOCV for all robotic assessment modules. The minimum $RMSE_{cv}$ value was 2.12 for Draw I module with a combination of Smoothness, Grasping, Hit wall score and Target reached kinematic variables, 3.02 for Draw Diamond module with a combination of Movement Time, Reaction Time, Path Ratio and Smoothness kinematic variables, and 2.79 for Draw Circle module with a combination of stability time, Movement Time, Reaction Time and Smoothness kinematic variables.

Table 2. $RMSE_{cv}$ Values for Four Combinations of Kinematic Variables for All Modules During LOOCV

Robotic Assessment Modules	Draw I	Draw Diamond	Draw Circle
$RMSE_{cv}$	2.12	3.02	2.79
Kinematic variables	Smoothness, Grasping, Hit Wall Score and Target Reached	Movement Time, Reaction Time, Path Ratio and Smoothness	Stability Time, Movement Time, Reaction Time and Smoothness

Performance of the prediction models to predict the MAS generated using four kinematic variables selected in the LOOCV process are shown in Table 3. Draw I model shows

the highest correlation between kinematic variables and MAS score in training (R_t=0.84) and validation (R_v=0.81) data sets than Draw Diamond model (R_t=0.63 for training and R_v=0.70 for validation) and Draw Circle model (R_t=0.71 for training and R_v=0.64 for validation). Besides, the Draw I model also shows the lowest RMSE in training (RMSE$_t$=1.85) and validation (RMSE$_v$=2.05) data sets, denoting higher accuracy compared to Draw Diamond model (RMSE$_t$=2.68 for training and RMSE$_v$=2.76 for validation) and Draw Circle model (RMSE$_t$=2.44 for training and RMSE$_v$=2.71 for validation).

Table 4 provides the movement descriptors used for the predictions and the corresponding coefficients. The Grasping variable provided the largest contribution in Draw I regression model, Movement Time variable provided largest contribution in the Draw Diamond regression model while movement time provided largest contribution in the Draw Circle model. Target reached gave the smallest contribution in Draw I regression model while reaction time gave the smallest contribution in both Draw Diamond and Draw Circle regression models. Even though the target reached and the reaction time were the smallest contributions in prediction models, removing them would cause the model's accuracy (RMSE$_v$) to reduce by more than 3%.

Table 3. Performance of The Regression Model

Outcome	Data set		Correlation coefficient		RMSE	
	Training	Validation	R_t	R_v	RMSE$_t$	RMSE$_v$
Draw I	28	14	0.84	0.81	1.85	2.05
Draw Diamond	28	14	0.63	0.70	2.68	2.76
Draw Circle	28	14	0.71	0.64	2.44	2.71

Abbreviations: RMSE$_t$, root mean square error training; RMSE$_v$, root mean square error validation; R_t, correlation coefficient in the training data set; R_v, correlation coefficient in the validation data set.

Table 4. Regression Models for MAS Outcome: Outcome = (Predictor1 x Coeff1) + (Predictor2 x Coeff2) + (Predictor3 x Coeff3) + (Predictor4 x Coeff4) + Constant

Robotic assessment module	Pre1 / Coeff 1 / (Scale)	Pre2 / Coeff 2 / (Scale)	Pre3 / Coeff 3 / (Scale)	Pre4 / Coeff 4 / (Scale)	Constant (Scale)
Draw I	HWS / 0.78 / (0.43)	TR / -0.58 / (-0.16)	Gr / 0.27 / (0.52)	Sm / $11.5x10^3$ / (0.35)	-16.89 / (0.27)
Draw Diamond	MT / 0.21 / (0.80)	RT / -2.74 / (-0.51)	PR / 0.32 / (0.76)	Sm / $95.1x10^3$ / (1.36)	-16.22 / (0.16)
Draw Circle	MT / 0.30 / (1.18)	RT / -1.09 / (-0.22)	ST / 0.09 / (0.78)	Sm / $67.3x10^3$ / (0.92)	-8.98 / (0.39)

Abbreviations: Pre1, Predictor1; Pre2, Predictor2; Pre3, Predictor3; Pre4, Predictor4; Coeff, Coefficient; HWS, Hit Wall Score; TR, Target Reached; Gr, Grasping; Sm, Smoothness; MT, Movement Time;, RT, Reaction Time; PR, Path Ratio; ST, Stability Time.

Highlighting the *R*-values is important because it represents the performance of relationship between generated model and the MAS score. The *R*-values were higher than *R*-value reported in the study of Lambercy *et. al.* [12] which used step-wise regression model to calculate MAS (*R*=0.599). Besides, previous studies [3,14,15,17-20,42] shows the correlation value of several clinical scales and kinematic variables ranged between 0.40 and 0.83. However, direct interpretation of *R*-value could lead to misinterpretation of the accuracy of the model [43]. This is due to different clinical scales used in the studies except study conducted by Lambercy *et. al.* [12] used MAS which is same clinical scale used in this study. Besides, the type of movements used were also different from this study. However, this study shows that by combining the reaching, hand rotation and grasping movements during the assessment process, it could provide higher correlation between clinical scale and kinematic variables.

In order to reduce the assessment time, the Draw Diamond and Draw Circle modules could be discarded from the task. It is because, these modules showed weak performance in predicting the MAS score, which suggested that these modules did not provide meaningful information to assess hand function. By reducing the robotic assessment module to only Draw I

module, it also reduces the number of exercises to be performed and evaluated, potentially simplifying patient evaluation and thus, reduce assessment time.

Before Draw I module can be used for assessment purposes, the correlations between MAS score and kinematic variables must be further increased. To do so, further studies must be conducted. On the other hand, with the current level of Draw I model performance, quantitative data from iRest could potentially be used for interim assessments, assuming that MAS was judged to be appropriate outcomes for the study.

6. Conclusion

The combination of three basic movements which are reaching, hand rotation and grasping in the device to assess the stroke patients provide better correlation in predicting the clinical assessment score compared to the devices that only allowed one or two of the movements. Besides, this study was able to show that a non-motorized device can provide inexpensive and practical way of conducting correlated assessments. The absence of actuation in the device could increase the safety, reduce the complexity of mechanical design and increase usage due to less supervision. The finding shows that the combination of the three basic movements and the unactuated device which allowed voluntary movement from the patient are the important parameter to be implemented in the objective assessment device.

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