Medical Engineering and Physics 71 (2019) 114–120

Contents lists available at ScienceDirect

Medical Engineering and Physics

journal homepage: www.elsevier.com/locate/medengphy

Technical note

Validation of computerized square-drawing based evaluation of motor function in patients with stroke

Milica S. Isaković [a,b,*], Andrej M. Savić [a,b], Ljubica M. Konstantinović [c,d], Mirjana B. Popović [a,e]

[a] School of Electrical Engineering, University of Belgrade, Bulevar kralja Aleksandra 73, 11000 Belgrade, Serbia
[b] Tecnalia, Health Division, Mikeletegi Pasealekua 1–3, 20009 Donostia-San Sebastian, Spain
[c] Faculty of Medicine, University of Belgrade, Dr Subotića 8, 11000 Belgrade, Serbia
[d] Clinic for Rehabilitation “Dr Miroslav Zotović”, Sokobanjska 13, 11000 Belgrade, Serbia
[e] Institute for Medical Research, University of Belgrade, Dr Subotića 4, 11000 Belgrade, Serbia

ARTICLE INFO

Article history:
Received 20 September 2018
Revised 4 April 2019
Accepted 7 June 2019

Keywords:
Motor function assessment
Upper limb
Drawing board
Stroke

ABSTRACT

Human-administered clinical scales are commonly used for quantifying motor performance and determining the course of therapy in post-stroke individuals. Computerized methods aim to improve consistency, resolution and duration of patients' evaluation. The objective of this study was to test the validity of computerized square-drawing test (DT) for assessment of shoulder and elbow function by using novel set of DT-based kinematic measures and explore their relation with Wolf Motor Function Test (WMFT) scoring. Forty-seven stroke survivors were tested before and after the rehabilitation program. DT involved drawing a square in horizontal plane using a mechanical manipulandum and a digitizing board. Depending on the initial classification of patients into low or high performance groups, the two different outcome metrics were derived from DT kinematic data for evaluation of each group. Linear regression models applied to map DT outcome values to WMFT scores for both groups resulted with high correlation coefficients and low mean absolute prediction error. In conclusion, we have identified a set of kinematic measures suitable for fast and objective motor function evaluation and functional classification, strongly correlating with WMFT score in post-stroke individuals. The results support validation of square-drawing motor function assessment, encouraging its use in clinical settings.

1. Introduction

Evaluating functional and motor abilities of the hemiplegic upper limb (UL) is of great importance for optimizing the rehabilitation strategy and predicting the course of regaining motor skills after stroke. Conventionally, assessment of UL is carried out by therapists using ordinal clinical scales: Fugl-Meyer Assessment (FMA) [1], Wolf Motor Function Test (WMFT) [2], Action Research Arm Test (ARAT) [3], Motor Power score (MP) [4], and Motor Status score (MS) [5]. Although these scales are standardized and validated, they may lack reproducibility due to subjective evaluation depending on the clinician's ability to observe subtle differences in motor functions [6]. These scales are time consuming, which discourages clinicians from their regular use to track the recovery in the rehabilitation process. Furthermore, their reliance on ordinal scales may lead to ceiling and floor effects and insensitivity to subtle changes in motor performance [7]. Consequently, the use of prognostic tests and indicators to prescribe therapeutic programs is still not a routine practice [8].

Robotic technology is an emerging field that has the potential to improve both therapy [9] and assessment [6] of paretic UL motor function, and it is well accepted and tolerated by patients [10]. In order to obtain objective, consistent, reproducible and fast quantitative evaluation, robotic methods for the UL assessment have been investigated [11–17].

One of investigated methods is the Drawing Test (DT), a simple and efficient technique first introduced as a measure of coordination of elbow and shoulder joints in the clinical trial evaluating functional electrical therapy [18]. The subjects were asked to draw a self-paced square with a side length of 20 cm on a digitizing board in the horizontal plane. Throughout the next decade DT was employed in a number of studies, both in healthy [19] and hemiplegic subjects [20–25]. Drawing the square was found to be cognitively demanding task for some patients, so the modified version of DT, testing radial point-to-point movements was employed in [15]. The kinematic outcome metrics showed strong correlation with Ashworth Scale, standard clinical measure of spasticity [15].

* Corresponding author at: School of Electrical Engineering, University of Belgrade, Bulevar kralja Aleksandra 73, 11000 Belgrade, Serbia.
E-mail address: isakovic@etf.rs (M.S. Isaković).

https://doi.org/10.1016/j.medengphy.2019.06.001
1350-4533/

Numerous studies investigated the correlations between robot-assessed movement descriptors and clinical scales in stroke or spinal cord injury population [26], such as FMA [11,12,16,27–31], MP [11,12,29], MS [11,12,16,28,29], ARAT [13,30,31] and WMFT [32,33]. However, the high cost of most robotic systems significantly impedes the validation of robotic assessment and wider use in standard clinical practice [6]. According to recent systematic review on kinematic measures for UL robot-assisted therapy following stroke and their correlations with clinical measures [26], most of the evaluated kinematic parameters were associated with the Body Functions and Structure domain of the International Classification of Functioning, Disability and Health (ICF) [34]. The authors concluded that more studies focusing on kinematic parameters associated with ICF Activity and Participation domains are needed [26].

The aim of this study was to define novel DT-based kinematic measures and investigate their relation with standard clinical assessment of UL motor function – WMFT. We hypothesized that there would be a strong correlation between DT and WMFT as these tests evaluate similar, simple shoulder/elbow movements in the horizontal plane performed by a subject seated in front of the table. To the best of our knowledge, this is the first evaluation of the relationship between WMFT and the robotic measurement of the UL movements involving the digital drawing board.

2. Methods

2.1. Subjects

Forty seven patients (gender: male/female 37/10, age: 57.6 ± 10.9 years, paretic arm: left/right 21/26, stage subacute/chronic 42/5, time since stroke onset: median [min–max] 51 [13–450] days) participated in the study. The subjects were recruited for the purpose of clinical study on robotic training and assessment [35] registered at the ClinicalTrials.gov (ID: NCT02729649). The study was conducted at the Clinic for Rehabilitation “Dr Miroslav Zotović”, Belgrade, Serbia and approved by the Local Ethics Committee. All participants signed an informed consent form and all research procedures were performed in accordance with the Declaration of Helsinki.

2.2. Protocol

DT and WMFT were performed before and after four weeks of rehabilitation program, provided 5 days per week. The subjects gave permission for video recordings of testing procedures.

2.2.1. The Wolf Motor Function Test

WMFT is an activity-based test comprising 15 timed functional tasks and 2 strength tasks. Each item is rated on a 6-point (from 0 to 5) Functional Ability Scale (FAS) and summed into total WMFT-FAS score [36]. WMFT has shown high test-retest and interrater reliability and validity for activity-based evaluation of UL function [37].

WMFT was evaluated by a physiotherapist experienced in neurological rehabilitation. WMFT-FAS score for 15 function-based tasks (maximum possible score of 75 points) was applied in further analysis.

2.2.2. The Drawing Test assessment

The setup consisted of the mechanical manipulandum with a handle [38], a wireless mouse attached to the handle, Intuos 4 XL drawing board (Wacom, Portland, USA) and a PC. The data were acquired with 100 Hz sampling frequency and 0.05 mm spatial resolution.

The subjects performed DT while seated in a chair with adjustable seat height positioned in front of the drawing board that was about 30 cm below the shoulder level (Fig. 1). The trunk was

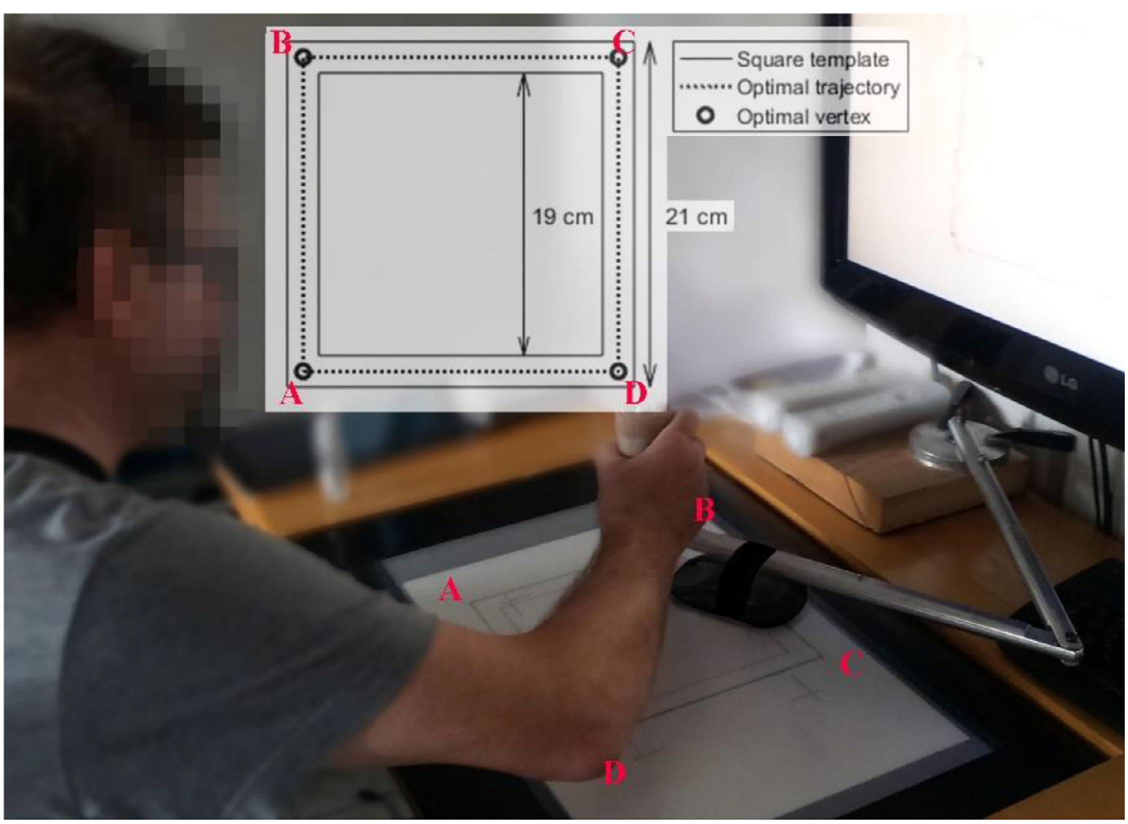

Figure 1. The measurement setup, the Drawing Test square template and the subject performing the movement with the affected right arm in the ABCDA direction.

secured in a harness to prevent compensatory body movements. Subjects performed planar movements while holding and pushing/pooling the handle of the manipulandum. The task was to draw a square within a presented template with affected UL, with maximal speed and precision. The template consisted of two concentric squares with side lengths of 19 cm and 21 cm (Fig. 1). The course of movements was from the proximal contra lateral corner (vertex A, Fig. 1) to the tested UL proceeding to the distal contra lateral corner, and continued to cover the complete the path between concentric squares.

The testing procedure was supervised by an experienced therapist. The subjects were repeating the trials of the DT as long as the therapist considered that they can perform better in terms of speed and precision (between 3 and 5 trials). The last performed trial was chosen for further analysis.

2.3. The Drawing Test outcome measures

Visual inspection of DT data and corresponding WMFT scores revealed two distinct characteristics of the trajectories performed by the subjects with low WMFT score (i.e. lower than 50% of maximum WMFT score): inability to reach 50% of the required range of motion in Y direction and/or inability to maintain the required horizontal BC direction. Following these observations, we introduced the initial classification based on two conditions: (1) the Y coordinate of DT data always below the middle of the template, and (2) the absolute value of the slope in BC direction greater than 10°. DT drawings were first tested for the condition (1), and in case it was fulfilled the DT trial was classified to Low Performance Group (LPG). Otherwise, if the maximum value of Y coordinates (the furthest point reached) of DT was above the middle of the template, DT drawing was segmented into four sides using an iterative algorithm for detection of vertices [25]. The slope in BC direction was calculated, and if its absolute value was greater than 10° (second condition fulfilled) the DT trial was also classified to LPG. If none of the two conditions was reached, the DT trial was classified to High Performance Group (HPG). The diagram of the initial classification to LPG or HPG and representative examples of DT trials for both groups labeled with relevant parameters and outcome measures are presented in Figure 2.

By applying the two rules, we singled out the DT trials that strongly differ from the square template (LPG). These trajectories were not represented with distinct vertices, sides of similar length and corners with angles close to 90°. This group of DT trials was characterized with only one outcome measure: normalized area within the template A_n, calculated as a ratio of the area within outer square template (gray area in Fig. 2 – LPG) and the area of outer square template (21×21 cm^2).

In case of HPG, a set of 14 outcome values of 5 geometric measures was defined:

1) Normalized area within the template A_n is calculated as the ratio of drawn area within outer square template (gray area in Fig. 2 – HPG) and the area of outer square template (21×21 cm^2).
2) Root Mean Square Error – *RMSE* assesses the deviation of the analyzed trajectory from the fitted lines (a_1, a_2, a_3, a_4 in Fig. 2) between the starting point and final position of the handle (four red vertices in Fig. 2) using linear regression, and is given by (1), where y and $\hat{y}$ denote observed and estimated data points, respectively.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}{n}} \quad (1)$$

RMSE was calculated for each side of the square and summed to obtain one outcome measure.

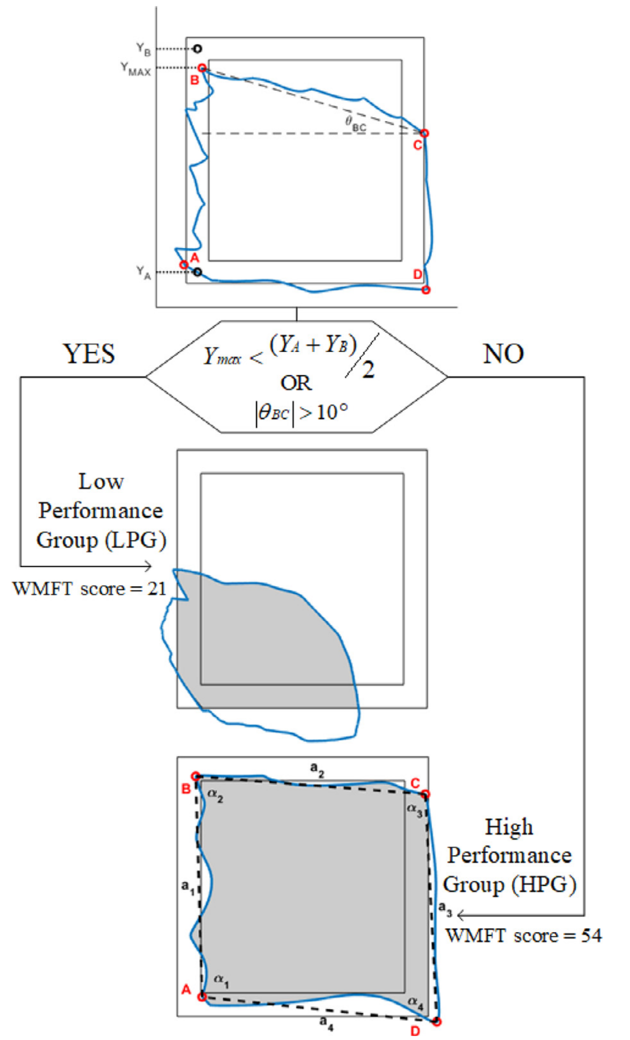

Figure 2. The diagram of the initial classification and representative examples of DT trials (blue line) for LPG and HPG with corresponding WMFT score. Vertices of DT trajectories are marked with red circles and labeled with matching letter. Vertices A and B of the "ideal" square trajectory are labeled on the top panel with black circles. Gray shaded area represents the covered area within the outer square template, for both LPG and HPG. For HPG, straight dashed lines are fitted between the trajectory vertices. The sides of the obtained quadrilateral are labeled with a_i and the angles are labeled with α_i.

3) Normalized side length (d_i, $i = 1$–4) is maximal (value of 1) when the length of the line fitted between two vertices a_i(a_i, $i = 1$–4 in Fig. 2 – HPG) is within the desired range [19–21 cm], and decreases for values out of this range. It is defined as:

$$d_i = \begin{cases} \frac{a_i}{19}, a_i < 19 \\ 1, 19 \le a_i \le 21 \quad, i = 1, \ldots, 4 \\ 2 - \frac{a_i}{21}, a_i > 21 \end{cases} \quad (2)$$

Indices i correspond to sides of the square (1 – AB, 2 – BC, 3 – CD, 4 – DA).

4) Absolute deviation from 90° (δ_i, $i = 1$–4) was calculated for each angle α_i(α_i, $i = 1$–4 corresponding to vertices A, B, C and D, respectively in Fig. 2 – HPG) as:

$$\delta_i = |\alpha_i - 90°|. \quad (3)$$

5) Spectral Arc Length – *SAL* metric assesses the smoothness of motion [39]. *SAL* is a dimensionless measure of the length of frequency spectrum curve of a speed profile over the band-

width appropriate for the action. It is defined as:

$$SAL_i = -\int_0^{\omega_c} \sqrt{\left(\frac{1}{\omega_c}\right)^2 + \left(\frac{d\hat{V}(\omega)}{d\omega}\right)^2}\, d\omega, i = 1, \ldots, 4 \quad (4)$$

where $[0,\ \omega_c]$ is the frequency band of interest (up to 20 Hz for normal human movement), indices i correspond to square sides, and the amplitude normalized Fourier magnitude spectrum of the velocity signal is given by:

$$\hat{V}(\omega) \triangleq \frac{V(\omega)}{V(0)} \quad (5)$$

2.4. Data analysis

The DT outcome measures calculation and statistical analysis were performed in Matlab (R2016a, The MathWorks Inc., Natick, USA). Two trials from one subject (before and after the rehabilitation program) were treated as independent observations. Therefore, the total number of analyzed trials was 94. The level of statistical significance was $p < 0.05$ (two-tailed).

Based on the video recordings of subjects performing DT and WMFT, we determined total duration of the tests and the time that the subject spent performing the tasks. Paired samples t-test was used to compare the two tests in terms of the subject performance time and the total test time.

Independent samples t-test was performed to compare WMFT score for two groups (LPG and HPG) obtained by initial classification.

For LPG, we used a simple linear regression model to map the DT outcome measure (area within the template) to WMFT score. WMFT score was defined with the regression Eq. (6):

$$WMFTscore = b_{A_n} A_n + Intercept, \quad (6)$$

where b_{An} is the regression coefficient for the variable A_n. To evaluate the performance, leave-one-out cross-validation was applied. This approach was chosen due to small number of trials in LPG. Each DT trial in turn was left out, a model was fitted to the remaining data, and the predicted WMFT value of the unused DT trail was computed.

For HPG, we used a multiple linear regression model to map 14 DT outcome values to WMFT score. WMFT score was defined with the regression Eq. (7):

$$WMFTscore = b_{A_n} A_n + b_{RMSE} RMSE + \sum_{i=1}^{4} b_{d_i} d_i + \sum_{i=1}^{4} b_{\delta_i} \delta_i + \sum_{i=1}^{4} b_{SAL_i} SAL_i + Intercept, \quad (7)$$

Where b_X (b_{An}, b_{RMSE}, ...) is the regression coefficient for the variable X (A_n, $RMSE$, ...). 10-fold cross-validation was performed to evaluate the performance. Each fold was once used as a validation set to compute the predicted WMFT score, while the remaining 9 folds formed the training set used to fit the model (determine the coefficients).

For both LPG and HPG, prediction errors between real and predicted WMFT score were calculated. The quality of the prediction was evaluated using the following metrics:

- Correlation coefficient (R-value) between real and predicted values of WMFT score
- The mean absolute value of the prediction error, using the model fitted on all data points.
- The mean absolute value of the prediction error obtained during cross-validation.

Compared to the cross-validation mean absolute prediction error, the value obtained using all data points is less rigorous estimation of the error. However, the comparison of two values provides valuable insight in the model: small difference between them suggests that the model will be able to generalize to new data and therefore have prognostic value, while large difference indicates that the model using all data points has over-fitted the data.

3. Results

Total time required for the implementation of the test (Fig. 3(A)), including positioning, instructions and demonstration

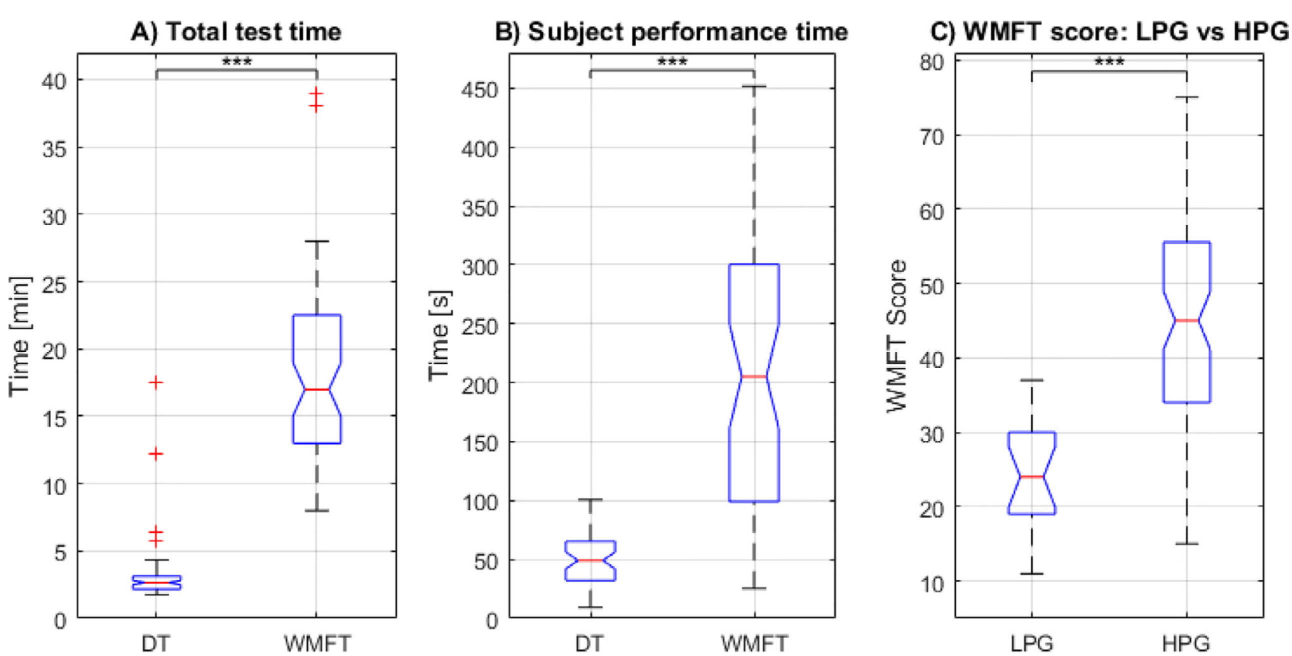

Figure 3. (A) Total time required for implementation of DT and WMFT. (B) Time subjects spent performing the tasks (movement duration) during DT and WMFT. (C) WMFT scores for Low Performance Group (LPG) and High Performance Group (HPG). Horizontal bars with asterisks indicate statistically significant difference between two conditions (***$p < 0.001$).

Table 1
Prediction quality metrics (correlation coefficient and mean absolute prediction errors for cross-validation and for all data points) for LPG and HPG regression models. Mean absolute prediction errors are expressed as values and a percentage of the maximum possible WMFT score.

Measure		LPG	HPG
Correlation coefficient (*R*-value)		0.88	0.74
Mean absolute prediction error (cross-validation)	Value	3.43	11.89
	Percentage of maximum possible score	4.57%	15.85%
Mean absolute prediction error (all data points)	Value	3.09	8.48
	Percentage of maximum possible score	4.12%	11.31%

by the tester and the subject performing the tasks, was significantly lower ($p < 0.001$) for DT (3.0 ± 1.9 min) compared to WMFT (17.9 ± 6.7 min). Also, there is significant difference in subject's task performance duration for the two tests (Fig. 3(B)). The subjects spent between 9.4 and 100.9 s (49.6 ± 22.3 s) when performing between 3 and 5 (on average 3.8) trials of DT, while the actual execution of 15 WMFT tasks (movement durations only, without breaks and instructions between the tasks) took on average 214.4 s (ranging from 25.4 s to 451.6 s).

Initial classification of DT trajectories (47 before and 47 after therapy: in total 94) based on two rules resulted with 18 trajectories assigned to LPG (10 before and 8 after therapy) and 76 trajectories assigned to HPG (37 before and 39 after therapy). Corresponding WMFT score (Fig. 3(C)) was significantly lower ($p < 0.001$) for LPG (24.6 ± 7.8) compared to HPG (45.2 ± 14.8).

Table 1 presents the prediction quality metrics for LPG and HPG: correlation coefficients between real and predicted WMFT scores, and mean absolute prediction errors, both for the models derived from all data points and for the cross-validation process. Prediction errors are expressed both as values and as percentage of maximum possible WMFT score. The *R*-value was greater than 0.7 for both groups (0.88 for LPG and 0.74 for HPG), indicating strong linear correlation [40].

4. Discussion

Although reliable and effective, clinical scales are technically demanding and time consuming (>20 min to complete) [41]. Recent survey among occupational and physical therapists showed that, although the majority of therapists reported having access to conventional assessment equipment (e.g. stopwatches, dynamometers, goniometers), less than 25% of them used any of these devices five or more times per week [42], mainly due to the lack of time. Fast and easy DT procedure, with average duration (including positioning and instructions) of 3 min, could allow therapists to perform daily assessments more efficiently. Time needed for patient to perform several trials of DT task (the movement only) is less than one minute (average 49.6 s). When compared to WMFT, DT required significantly less time to implement and perform (Fig. 3(A) and (B)). This significant reduction of performance time compared to WMFT is important for avoiding fatigue, a common condition in post-stroke individuals [43].

The initial DT trials based classification resulted in two groups (LPG and HPG). Analyses of corresponding WMFT scores for these two groups showed significant difference in average WMFT score (Fig. 3(C)), thus confirming the classification accuracy of each subjects' assignment to either LPG or HPG.

DT outcome values were defined according to the functional abilities of each subject, as determined during initial classification. The two rules for including a DT trial in LPG impose reduced resemblance of the drawn shape to a quadrilateral. Consequently, DT trials classified to LPG are quantified with a single outcome measure related to active range of motion. DT trials from HPG are represented with a broad spectrum of outcome values (14 values related to 5 different measures) to capture the finesse of high function movements. Some of these measures were used in previous studies on reaching impairment (smoothness [11–13,16,25,44], RMSE [11,13]), while the rest were introduced in this study as a measure of similarity between the drawn trajectory and the square template.

The proposed DT-based measures were validated using linear regression models. DT outcome values (normalized area within the template for LPG and set of 14 values for HPG) were mapped to WMFT score. As a result, the predicted WMFT score strongly correlates with real WMFT score for both groups. High values of the correlation coefficients (0.88 for LPG and 0.74 for HPG) obtained in the cross-validation procedure suggest that the proposed measures are sensitive to UL motor functions. Mean absolute prediction errors obtained during cross-validation (4.57% for LPG and 15.85% for HPG) were slightly higher than the prediction errors obtained using the regression model with all data points (4.12% for LPG and 11.31% for HPG). Small difference indicates the qualitative accuracy of the results. However, the regression model coefficients could be fine-tuned by analyzing a larger dataset. The high correlation between DT and WMFT and small prediction error obtained for LPG suggest that DT procedure could be particularly beneficial for patients with severe disability in the process of rehabilitation.

An objective quantification of UL functions contributes to better understanding of patient's condition, which is essential for deciding on the further course of therapy. Various studies examining different types of therapy (FES [20], robot-assisted therapy [45], CIMT [46], intensive physical treatment [47]) have shown that patients' reaction to therapy and course of recovery vary depending on their baseline condition. The proposed DT-based initial classification allows fast and effective assignment of patients to low or high performance group, therefore providing guidelines for selecting an adequate treatment intensity.

WMFT was chosen as the reference clinical scale for the validation purpose in several recent studies concerning robotic and computerized UL motor function assessment [32,33]. Within the ICF categorization of scales used in robot rehabilitation studies, the WMFT assesses changes in functional activities, while many commonly used scales (FMA, MSS, MAS) focus on motor impairment related to the body functions [48]. Moreover, Kwakkel et al. [9] recommend using valid instruments that measure UL skills specifically, such as WFMT, in studies on robot-assisted therapy. Also, some WMFT tasks comprise shoulder/elbow movements in the horizontal plane, similar to the DT task. Therefore, the selection of WMFT was appropriate for the validation of DT in our study. However, in order to precisely track the recovery of UL motor functions, the relationship between DT and other clinical assessment scores has yet to be identified, and this study is a step towards this goal.

Digitizing tablets have been used as tools for evaluation of visual control of arm movement [49], kinesthesia [50] and motor blocks [51] during point-to-point hand movements in Parkinson's disease. One of its most prominent applications is the spiral analysis, validated technique for quantifying movement disorders in patients with essential tremor [52] and PD [53,54]. Evaluation techniques based on the digitizing tablet are safe, portable, inexpensive, efficient, reproducible, noninvasive and easy to administer. The proposed DT task is simple, short and non-exhaustive for patients. The proposed methodology requires from subjects to hold the handle of the manipulandum, therefore demanding some level of preserved hand function. This can be easily overcome for subjects without voluntary grasping by bandaging the affected hand to the handle. Moreover, the square-drawing task in the horizontal plane does not necessarily require the usage of the digitizing tablet, since it can be easily incorporated in the majority of systems for robot-based therapy and assessment.

5. Conclusion

The proposed kinematic parameters offer a precise quantitative assessment of the UL motor functions adjusted to patients' abilities and highly correlates with a reliable and commonly used WMFT. The ease of implementation as a task for various robotic systems for therapy and assessment and strong correlation to WMFT score and comprehensiveness of the novel analysis, imply that the presented method has a great potential in clinical application for functional classification and evaluation of stroke patients. These results are a step towards new DT-based kinematic parameters, in line with the unmet need for integrated, optimized and enhanced clinical assessment of UL motor functions following stroke.

Acknowledgments

The authors would like to thank all patients and clinical personnel from the Clinic for Rehabilitation "Dr Miroslav Zotović" who participated in this study.

Conflicts of interest

None.

Funding

The research was partially supported by the Ministry of Education, Science and Technological Development, Republic of Serbia (Project no. 175016).

Ethical approval

The study was approved by the Ethics Committee of the Clinic for Rehabilitation "Dr Miroslav Zotović" affiliated with the Faculty of Medicine, University of Belgrade, Serbia.

References

[1] Fugl-Meyer AR, Jääskö L, Leyman I, Olsson S, Steglind S. The post-stroke hemiplegic patient. 1. A method for evaluation of physical performance. Scand J Rehabil Med 1975;7:13–31.
[2] Wolf SL, Lecraw DE, Barton LA, Jann BB. Forced use of hemiplegic upper extremities to reverse the effect of learned nonuse among chronic stroke and head-injured patients. Exp Neurol 1989;104:125–32. doi:10.1016/S0014-4886(89)80005-6.
[3] Lyle RC. A performance test for assessment of upper limb function in physical rehabilitation treatment and research. Int J Rehabil Res 1981;4:483–92. doi:10.1097/00004356-198112000-00001.
[4] Volpe B, Krebs H, Hogan N, Edelstein L, Diels C, Aisen M. A novel approach to stroke rehabilitation robot-aided sensorimotor stimulation. Neurology 2000;54:1938–44. doi:10.1212/WNL.54.10.1938.
[5] Carr JH, Shepherd RB, Nordholm L, Lynne D. Investigation of a new motor assessment scale for stroke patients. Phys Ther 1985;65:175–80. doi:10.1093/ptj/65.2.175.
[6] Scott SH, Dukelow SP. Potential of robots as next-generation technology for clinical assessment of neurological disorders and upper-limb therapy. J Rehabil Res Dev 2011;48:335–54. doi:10.1682/JRRD.2010.04.0057.
[7] Krakauer JW. Arm function after stroke: from physiology to recovery. Semin Neurol 2005;25:384–95. doi:10.1055/s-2005-923533.
[8] Coupar F, Pollock A, Rowe P, Weir C, Langhorne P. Predictors of upper limb recovery after stroke: a systematic review and meta-analysis. Clin Rehabil 2012;26:291–313. doi:10.1177/0269215511420305.
[9] Kwakkel G, Kollen BJ, Krebs HI. Effects of robot-assisted therapy on upper limb recovery after stroke: a systematic review. Neurorehabil Neural Repair 2008;22:111–21. doi:10.1177/1545968307305457.
[10] Mazzoleni S, Turchetti G, Palla I, Posteraro F, Dario P. Acceptability of robotic technology in neuro-rehabilitation: preliminary results on chronic stroke patients. Comput Methods Programs Biomed 2014;116:116–22. doi:10.1016/j.cmpb.2013.12.017.
[11] Colombo R, Pisano F, Micera S, Mazzone A, Delconte C, Carrozza MC, et al. Robotic techniques for upper limb evaluation and rehabilitation of stroke patients. IEEE Trans Neural Syst Rehabil Eng 2005;13:311–24. doi:10.1109/TNSRE.2005.848352.
[12] Bosecker C, Dipietro L, Volpe B, Igo Krebs H. Kinematic robot-based evaluation scales and clinical counterparts to measure upper limb motor performance in patients with chronic stroke. Neurorehabil Neural Repair 2010;24:62–9. doi:10.1177/1545968309343214.
[13] Zariffa J, Kapadia N, Kramer JL, Taylor P, Alizadeh-Meghrazi M, Zivanovic V, et al. Relationship between clinical assessments of function and measurements from an upper-limb robotic rehabilitation device in cervical spinal cord injury. IEEE Trans Neural Syst Rehabil Eng 2012;20:341–50. doi:10.1109/TNSRE.2011.2181537.
[14] Hussain A, Budhota A, Hughes CML, Dailey WD, Vishwanath DA, Kuah CW, et al. Self-paced reaching after stroke: a quantitative assessment of longitudinal and directional sensitivity using the H-man planar robot for upper limb neurorehabilitation. Front Neurosci 2016;10. doi:10.3389/fnins.2016.00477.
[15] Eder CF, Popović MB, Popović DB, Stefanović A, Schwirtlich L, Jović S. The drawing test: assessment of coordination abilities and correlation with clinical measurement of spasticity. Arch Phys Med Rehabil 2005;86:289–95. doi:10.1016/j.apmr.2004.04.045.
[16] Colombo R, Sterpi I, Mazzone A, Delconte C, Minuco G, Pisano F. Measuring changes of movement dynamics during robot-aided neurorehabilitation of stroke patients. IEEE Trans Neural Syst Rehabil Eng 2010;18:75–85. doi:10.1109/TNSRE.2009.2028831.
[17] Kim H, Miller LM, Fedulow I, Simkins M, Abrams GM, Byl N, et al. Kinematic data analysis for post-stroke patients following bilateral versus unilateral rehabilitation with an upper limb wearable robotic system. IEEE Trans Neural Syst Rehabil Eng 2013;21:153–64. doi:10.1109/TNSRE.2012.2207462.
[18] Popovic DB, Popovic MB, Sinkjær T. Neurorehabilitation of upper extremities in humans with sensory-motor impairment. Neuromodulation 2002;5:54–66. doi:10.1046/j.1525-1403.2002._2009.x.
[19] Vuillermot S, Pescatore A, Holper L, Kiper DC, Eng K. An extended drawing test for the assessment of arm and hand function with a performance invariant for healthy subjects. J Neurosci Methods 2009;177:452–60. doi:10.1016/j.jneumeth.2008.10.018.
[20] Popovic MB, Popovic DB, Sinkjær T, Stefanovic A, Schwirtlich L. Clinical evaluation of functional electrical therapy in acute hemiplegic subjects. J Rehabil Res Dev 2003;40:443. doi:10.1682/JRRD.2003.09.0443.
[21] Popović D, Popović M, Sinkjær T, Stefanovic A, Schwitlich L. Therapy of paretic arm in hemiplegic subjects augmented with a neural prosthesis: a cross-over study. Can J Physiol Pharmacol 2004;82:749–56. doi:10.1139/y04-057.
[22] Popović DB, Sinkjær T, Popović MB. Electrical stimulation as a means for achieving recovery of function in stroke patients. NeuroRehabilitation 2009;25:45–58. doi:10.3233/NRE-2009-0498.
[23] Plavšić A, Švirtlih L, Stefanović A, Jović S, Đurović A, Popović M. Effects of functional electrical therapy on upper extremity functional motor recovery in patients after stroke: our experience and future directions. Med Pregl 2011;64:299–303. doi:10.2298/MPNS1106299P.
[24] Popović MB, Popović DB. Functional Electrical Therapy of Upper Extremities. In: Farina D, Jensen W, Akay M, editors. Introduction to neural engineering for motor rehabilitation. John Wiley & Sons; 2013. p. 477–92. doi:10.1002/9781118628522.ch24.
[25] Kostić MD, Popović MD. The modified drawing test for assessment of arm movement quality. J Automat Contr 2013;21:49–53. doi:10.2298/JAC1301049K.
[26] Do Tran V, Dario P, Mazzoleni S. Kinematic measures for upper limb robot-assisted therapy following stroke and correlations with clinical outcome measures: a review. Med Eng Phys 2018;53:13–31. doi:10.1016/j.medengphy.2017.12.005.
[27] Rohrer B, Fasoli S, Krebs HI, Hughes R, Volpe B, Frontera WR, et al. Movement smoothness changes during stroke recovery. J Neurosci 2002;22:8297–304. doi:10.1523/JNEUROSCI.22-18-08297.2002.
[28] Chang J-J, Yang Y-S, Wu W-L, Guo L-Y, Su F-C. The constructs of kinematic measures for reaching performance in stroke patients. J Med Biol Eng 2008;28:65–70.
[29] Colombo R, Pisano F, Micera S, Mazzone A, Delconte C, Carrozza M, et al. Assessing mechanisms of recovery during robot-aided neurorehabilitation of the upper limb. Neurorehabil Neural Repair 2008;22:50–63. doi:10.1177/1545968307303401.
[30] Celik O, O'Malley MK, Boake C, Levin HS, Yozbatiran N, Reistetter TA. Normalized movement quality measures for therapeutic robots strongly correlate with clinical motor impairment measures. IEEE Trans Neural Syst Rehabil Eng 2010;18:433–44. doi:10.1109/TNSRE.2010.2047600.
[31] McKenzie A, Dodakian L, See J, Le V, Quinlan EB, Bridgford C, et al. Validity of robot-based assessments of upper extremity function. Arch Phys Med Rehabil 2017;98:1969–76 e2. doi:10.1016/j.apmr.2017.02.033.
[32] Longhi M, Merlo A, Prati P, Giacobbi M, Mazzoli D. Instrumental indices for upper limb function assessment in stroke patients: a validation study. J Neuroeng Rehabil 2016;13:52. doi:10.1186/s12984-016-0163-4.
[33] Otaka E, Otaka Y, Kasuga S, Nishimoto A, Yamazaki K, Kawakami M, et al. Clinical usefulness and validity of robotic measures of reaching movement in hemiparetic stroke patients. J Neuroeng Rehabil 2015;12:66. doi:10.1186/s12984-015-0059-8.
[34] Organization WH. International classification of functioning, disability and health. ICF: Geneva: World Health Organization; 2001.

[35] Tomić TJD, Savić AM, Vidaković AS, Rodić SZ, Isaković MS, Rodríguez-de-Pablo C, et al. ArmAssist robotic system versus matched conventional therapy for poststroke upper limb rehabilitation: a randomized clinical trial. BioMed Res Int 2017:7659893. doi:10.1155/2017/7659893.
[36] Wolf SL, Thompson PA, Morris DM, Rose DK, Winstein CJ, Taub E, et al. The EXCITE trial: attributes of the Wolf Motor Function Test in patients with subacute stroke. Neurorehabil Neural Repair 2005;19:194–205. doi:10.1177/1545968305276663.
[37] Morris DM, Uswatte G, Crago JE, Cook EW, Taub E. The reliability of the Wolf Motor Function Test for assessing upper extremity function after stroke. Arch Phys Med Rehabil 2001;82:750–5. doi:10.1053/apmr.2001.23183.
[38] Popović MD, Kostić MD, Rodić SZ, Konstantinović LjM. Feedback-mediated upper extremities exercise: increasing patient motivation in poststroke rehabilitation. BioMed Res Int vol 2014:520374. doi:10.1155/2014/520374.
[39] Balasubramanian S, Melendez-Calderon A, Burdet E. A robust and sensitive metric for quantifying movement smoothness. IEEE Trans Biomed Eng 2012;59:2126–36. doi:10.1109/TBME.2011.2179545.
[40] Ratner B. The correlation coefficient: its values range between$+$ 1/$-$ 1, or do they? J Target Meas Anal Market 2009;17:139–42. doi:10.1057/jt.2009.5.
[41] Sun Z, Yue Y, Leung C, Chan M, Gelb A. China SGfPSI. Clinical diagnostic tools for screening of perioperative stroke in general surgery: a systematic review. Br J Anaesth 2016;116:328–38. doi:10.1093/bja/aev452.
[42] Langan J, Subryan H, Nwogu I, Cavuoto L. Reported use of technology in stroke rehabilitation by physical and occupational therapists. Disabil Rehabil Assist Technol 2017;13:641–7. doi:10.1080/17483107.2017.1362043.
[43] Choi-Kwon S, Kim JS. Poststroke fatigue: an emerging, critical issue in stroke medicine. Int J Stroke 2011;6:328–36. doi:10.1111/j.1747-4949.2011.00624.x.
[44] Kamper DG, McKenna-Cole AN, Kahn LE, Reinkensmeyer DJ. Alterations in reaching after stroke and their relation to movement direction and impairment severity. Arch Phys Med Rehabil 2002;83:702–7. doi:10.1053/apmr.2002.32446.
[45] Johnson MJ, Feng X, Johnson LM, Winters JM. Potential of a suite of robot/computer-assisted motivating systems for personalized, home-based, stroke rehabilitation. J Neuroeng Rehabil 2007;4:6. doi:10.1186/1743-0003-4-6.
[46] Taub E, Morris DM. Constraint-induced movement therapy to enhance recovery after stroke. Curr Atheroscler Rep 2001;3:279–86. doi:10.1007/s11883-001-0020-0.
[47] Smith D, Goldenberg E, Ashburn A, Kinsella G, Sheikh K, Brennan P, et al. Remedial therapy after stroke: a randomised controlled trial. Br Med J (Clin Res Ed) 1981;282:517–20. doi:10.1136/bmj.282.6263.517.
[48] Sivan M, O'Connor RJ, Makower S, Levesley M, Bhakta B. Systematic review of outcome measures used in the evaluation of robot-assisted upper limb exercise in stroke. J Rehabil Med 2011;43:181–9. doi:10.2340/16501977-0674.
[49] Klockgether T, Dichgans J. Visual control of arm movement in Parkinson's disease. Mov Disord 1994;9:48–56. doi:10.1002/mds.870090108.
[50] Klockgether T, Borutta M, Rapp H, Spieker S, Dichgans J. A defect of kinesthesia in Parkinson's disease. Mov Disord 1995;10:460–5. doi:10.1002/mds.870100410.
[51] Popovic MB, Dzoljic E, Kostic V. A method to assess hand motor blocks in Parkinson's disease with digitizing tablet. Tohoku J Exp Med 2008;216:317–24. doi:10.1620/tjem.216.317.
[52] Haubenberger D, Kalowitz D, Nahab FB, Toro C, Ippolito D, Luckenbaugh DA, et al. Validation of digital spiral analysis as outcome parameter for clinical trials in essential tremor. Mov Disord 2011;26:2073–80. doi:10.1002/mds.23808.
[53] Pullman SL. Spiral analysis: a new technique for measuring tremor with a digitizing tablet. Mov Disord 1998;13:85–9. doi:10.1002/mds.870131315.
[54] Westin J, Ghiamati S, Memedi M, Nyholm D, Johansson A, Dougherty M, et al. A new computer method for assessing drawing impairment in Parkinson's disease. J Neurosci Methods 2010;190:143–8. doi:10.1016/j.jneumeth.2010.04.027.