Prediction of Stroke-related Diagnostic and Prognostic Measures Using Robot-Based Evaluation

Sayyed Mostafa Mostafavi, Janice I. Glasgow, Sean P. Dukelow, Stephen H. Scott and Parvin Mousavi, *Senior Member IEEE*

Abstract— Traditional clinical scores for assessment of impairments resulting from stroke are inherently subjective and limited by inter-rater and intra-rater reliability. In contrast, robotic technologies provide objective, highly repeatable tools for quantification of motor performance of stroke subjects. Although use of robotic technologies has been widely suggested in the literature, they are not an established tool and their relationship to traditional clinical scales for stroke diagnosis and prognosis is mostly unknown. In this study we propose the application of two non-linear system identification methods, Parallel Cascade Identification and Fast Orthogonal Search, for prediction of stroke-related clinical scores using robot-based metrics. We show the suitability of these two methods for prediction of both diagnostic and prognostic scores. We compare our results with a previously applied approach based on linear regression and show the superiority of our modeling approach. Our results also underscore the importance of quantifying proprioceptive deficits in the prediction of motor-related prognosis scores.

Keywords—Stroke Assessment, Prognosis, Proprioception, Robot-Based Evaluation

I. Introduction

A cerebrovascular accident, otherwise known as stroke, creates a localized disruption of blood flow to brain tissues and often leads to a loss of brain function [1]. The disruption can be a result of thrombosis, embolism, or hemorrhage and can lead to tissue damage or cell death. The severity of damage to the brain tissue varies depending on the size and location of the lesion. The damage caused to the brain may lead to death or chronic conditions such as sensorimotor or proprioceptive impairments in upper and lower limbs [2].

A number of studies have concluded that a substantial portion of functional recovery is completed in the early weeks and month post stroke [3, 4]. This provides only a limited time window for clinicians to assess the damage to the brain and decide on a course of rehabilitation treatment, in order to maximize the chances of a patient's return to their pre-stroke conditions. The rehabilitation treatment is usually focused on targeted areas, which are assumed to be affected. The overall success of the rehabilitation process and the length of treatment are determined by continued observation and assessment of stroke subjects on a set of clinical scores [5]. These scores classically target quantification of either neurological impairments or disability. Whereas impairment generally refers to change in a particular function of the brain (e.g. loss of vision), disability or activity limitation denotes the (in)ability of an individual to perform their activities of daily living (e.g. grooming). If measured at hospital intake, the clinical scores can serve as a diagnostic measure of the severity of stroke. Measurements at hospital discharge are often viewed as how well stroke patients have functionally recovered post stroke, and are hence prognostic measures. The length of hospital stay, henceforth referred to as *Length-of-Stay*, is itself another important prognostic measure.

Examples of diagnostic scores used for assessment of impairments include *the Modified Ashworth score* [8], the *Chedoke-McMaster Stroke Assessment* [16] and the *Purdue Pegboard* score[1] [7]. An example of a clinical score used to assess activities of daily living (ADL) is the *Functional Independence Measure (FIM)* [6]. FIM evaluates 18 ADL tasks rated on a 1-7 scale, categorized into 13 motor and 5 cognitive items. The maximum total score for the collection of total and motor items is 126 (18*7) and 91 (13*7). These two are referred to as *FIM-Total* and *FIM-Motor* scores, respectively.

These clinical scores tend to rely on observer based ordinal scales, many of which have limited inter-rated and intra-rater reliability [9]. To address these limitations, robotic technologies capable of recording objective, highly repeatable data for assessment of sensorimotor impairments have been developed [10]. KINARM (Kinensiological Instrument for Normal and Altered Reaching Movements, BKIN Technologies, Kingston, ON) is one such robotic device that quantifies both sensorimotor and proprioceptive performance [17].

In recent research, the relationship between the robotic measures and clinical scores has been explored. Bosecker *et al.* have used linear regression (LR) to model and estimate

This work is supported by the Natural Sciences and Engineering Research Council of Canada (NSERC).

Sayyed Mostafa Mostafavi, Parvin Mousavi, and Janice I. Glasgow are with School of Computing, Queen's University, Kingston, Ontario, Canada

Sean P. Dukelow is with Department of Clinical Neurosciences, University of Calgary, Calgary, AB, Canada

Stephen H. Scott is with Centre for Neuroscience Studies, Queen's University, Kingston, Ontario, Canada

Sayyed Mostafa Mostafavi is the corresponding author. mostafa@cs.queensu.ca

[1] Purdue Pegboard is predominantly a research-based score and is not often used in clinical practice.

978-1-4673-6024-1/13/$31.00 ©2013 IEEE

stroke-related clinical scores using sensorimotor robot-based evaluation scales [11]. The predicted scores in this study are all diagnostic and there is no suggestion in the literature on how robot-based evaluation metrics relate to stroke prognosis. Furthermore, a recent study suggests that proprioceptive and sensorimotor deficits following stroke are independent [18]. As such, it is of interest to estimate diagnostic and, importantly, prognostic clinical scores using metrics that quantify sensorimotor and proprioceptive performance. Finally, the question of estimating stroke-related scores using non-linear models has not been investigated.

In the present work, we use the KINARM exoskeleton robot to quantify both limb sensorimotor skills and proprioceptive function after stroke. We then use two non-linear system identification methods, Parallel Cascade Identification (PCI) and Fast Orthogonal Search (FOS), for estimation of stroke-related diagnostic and prognostic scores. Specifically, we use robot-based metrics to predict *FIM-Motor*, *FIM-Total, Purdue Pegboard* and *Modified Ashworth* Score at hospital intake as diagnostic measures and *FIM-Motor* and *FIM-Total* at hospital discharge along with *Length-of-Stay* as prognostic scores. We show that the non-linear techniques have the potential to make more accurate predictions of clinical scores than simple linear regression [11].

II. MATERIALS AND METHODS

A. Participants and Robotic Tasks

One hundred ischemic and 26 hemorrhagic stroke patients were recruited after admission to St. Mary's of the Lake Hospital (Kingston, ON, Canada) and Foothills Hospital (Calgary, AB, Canada) for clinical stroke assessment and robotic evaluation using the KINARM exoskeleton robotic device. The study was approved by the institutional ethics review boards and all subjects for the study provided their informed consent to participate in the study.

Robotic metrics were recorded for two tasks. Motor performance was evaluated by a visually guided reaching task: with full vision, subjects were asked to reach "quickly and accurately" from a central target to one of eight peripheral targets located 10 *cm* away, distributed around the circumference of a circle. Each trial began with subjects holding their index finger tip at the central target for 1250-1750 *ms*. Then a peripheral target was illuminated and subjects were given 3000 *ms* to complete the reach. Each target was presented once per block and subjects completed eight blocks for a total of 64 trials. For each subject, the value of each measured parameter over 64 trials was averaged and used. Subjects performed this task with both the affected and unaffected arm. A total of twelve movement parameters were recorded in each trial. These parameters can be categorized into five major attributes related to sensorimotor control: (1) upper-limb postural control, (2) reaction time, (3) initial movement, (4) corrective movements, and (5) total movement metrics. Robotic parameters within each of the above five attribute categories (in order) are as follows: (1) postural hand speed; (2) reaction time, and no reaction time; (3) initial movement direction error, initial movement ratio, and hand speed ratio; (4) number of speed peaks, differences between speed maxima and minima, and no movement end; (5) movement time, hand path length, and maximum hand speed. Details of these parameters are described in [9].

Proprioceptive function was assessed by an arm-position matching task: subjects allowed the robot to passively move one hand to one of nine different spatial locations on one side of the body with vision occluded. When the robot stopped, subjects attempted to move the opposite (active) hand to the mirror location in space. When subjects reported they attained the mirror location, the next trial began. Target locations were such that the outer eight targets were separated by 10 *cm*. Each subject completed six blocks (target locations random within a block) for a total of 54 trials. For each subject, the value of each measured parameter over 54 trials was averaged and used. The robot moved the affected arm and the subject actively moved the less affected arm to match the limb position. A total of nine parameters quantifying arm-matching position sense are recorded on the KINARM robot. These nine parameters are categorized within three major parameter attributes: (1) trial-to-trial variability of the active hand in x, y and xy directions (Var_x, Var_y, Var_{xy}); (2) contraction/expansion of the overall spatial area of the active hand relative to the passive hand in x, y and xy directions ($Area_x$, $Area_y$, $Area_{xy}$); and (3) systematic shift between the passive and active hand in x, y and xy directions ($Shift_x$, $Shift_y$, $Shift_{xy}$). A more detailed description of the task and its associated parameters can be found in [15].

B. Fast Orthogonal Search (FOS)

A system identification method, FOS [13], was used to identify the most informative robotic metrics that contribute towards prediction of seven diagnostic and prognostic clinical scores. FOS allows building a non-linear approximation of input terms to best predict a desired target value [13]:

$$y(n) = \sum_{m=1}^{M} a_{\mathrm{m}}\, \mathrm{p}_m(n) + e(n) \qquad (1)$$

where *y(n)* is the target function, p_m are the basis functions with their associated coefficients a_m , and *e(n)* represents the estimation error.

In this study, the seven diagnostic and prognostic scores were used individually as target functions. The robotic measurements from both the visually-guided reaching and the arm-position matching tasks, and their non-linear transformations constitute the input functions.

FOS searches through all "*N*" input candidate basis functions, where *N>>M* and iteratively picks those candidates which contribute the largest error reduction as measured by the mean square error (MSE). MSE is calculated as the difference between the model estimate and the actual output. The basis of FOS is Gram-Schmidt orthogonalization, whereby orthogonal basis functions are generated from the $p_m(n)$ and

coefficients are found such that the MSE of the output estimation is minimized. While orthogonal basis functions are computationally expensive and time-consuming to calculate, FOS overcomes this problem by only calculating the coefficients of each orthogonal function, thus providing a quick method of model generation [14].

The first function selected by any model using FOS is assigned a value of 1, with a coefficient term that accounts for the constant term in the model. Following this first iteration, all subsequent basis functions are chosen from the provided pool of candidates. Non-linearity was introduced into our predicted models by including *squared, cubic, sin, cosine,* and *logarithmic* functions of the robotic metrics. When a function is selected, it is removed from the candidate pool so that it will not be selected again for that particular model. A detailed description of this method is presented in [13].

FOS has the advantage over simple models such as linear regression, as used in [11], in that it allows building non-linear models, thus providing a potentially more accurate approximation of the clinical score. Moreover, the orthogonality of the picked candidate functions means that there is minimal dependency between the chosen robotic metrics for each model prediction.

C. Parallel Cascade Identification (PCI)

PCI is used to model the input/output relationship in a non-linear system [12]. This method constructs a sum of cascades, each consisting of a dynamic linear element followed by a static non-linear element, as described in figure 1. A first approximation of the non-linear system is found using the first cascade. The residue, $y_1(n)$, is calculated as the difference between the desired system output and the output of the first cascade $z_1(n)$. This calculated residue is treated as a new non-linear system and fed into the second cascade to find a new approximation for the input residue. This procedure is repeated until the output residue of the final cascade is smaller than a predefined approximation error.

The dynamic linear component of PCI is often used for modeling of signals that vary over a time course (i.e. time-series data). For our application, prediction of every clinical score is purely based on the robotic measurements for a particular individual and does not depend on the remaining robotic measurements for the rest of the population. As such, we use a simplification of PCI in which we do not use the dynamic aspect of this modeling approach.

The estimated output of a PCI model, denoted by $\hat{y}(n)$, is the sum of the outputs from all of the cascades:

$$\hat{y}(n) = \sum_{k=1}^{I} (z_i(n)) \qquad (2)$$

where *I* is the number of cascades.

In this study, inputs to the PCI model are the robotic metric measurements from both the visually-guided reaching and arm-position matching tasks and the output is the predicted score. As a result a multiple-input single output

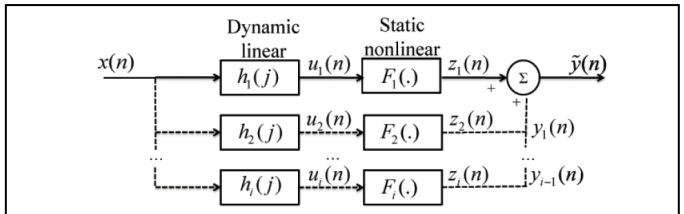

Figure 1. A Typical PCI Model [19]

(MISO) PCI model is built. The large pool of twelve reaching and nine position-matching robotic metrics were preprocessed prior to being used as inputs to the PCI algorithm. Our analysis with FOS indicated that six or less robotic metrics are selected for non-linear model estimations. As such, we used a total of six inputs for the PCI model. Correlation analysis was performed and six robotic metrics that had the highest correlation coefficient for each clinical score prediction were picked. For training a MISO PCI algorithm, one of the inputs, say x_1, is chosen at random. The remaining five inputs, $x_2, \ldots, x_6$ can then contribute to the output of the dynamic linear block for the i^{th} cascade, denoted by $u_i(n)$, which is given by:

$$u_i(n) = h_i(0)\, x_1(n) + C \sum_{i=2}^{6} (x_i(n)) \qquad (3)$$

.

where $C = \frac{y_{i-1}^2(n)}{y^2(n)}$ and $h_i(0)$ is constructed using:

$$h_i(0) = (1/T+1) \sum_{n=0}^{T} y_{i-1}(n) x(n) \qquad (4)$$

Non-linearity is introduced into the model by the static non-linear component. This is done by fitting a polynomial from the input $u_i(n)$ to the residue $y_{i-1}(n)$. The output of the i^{th} cascade, $z_i(n)$, is then given by:

$$z_i(n) = F_i(u_i) = \sum_{j=0}^{M} a_{ij} u_i^{\,j} \qquad (5)$$

where *M* is the polynomial degree and a_{ij} are the polynomial coefficients that minimize the root-mean-square error for the estimation of the i^{th} cascade. In the current study, we use 3rd degree polynomials, thus we set *M = 3*. The residue of the i^{th} cascade, used as the target estimation of the next cascade is given by:

$$y_i(n) = y_{i-1}(n) - z_i(n) \qquad (6)$$

The addition of a new cascade is stopped when either a predefined maximum number of cascades is reached or the estimation error of the system is smaller than a given threshold. A more detailed description of nonlinear system identification using PCI is given in [12].

D. Modeling and Performance Evaluation

FOS, PCI, and LR were used to model and predict all seven diagnostic and prognostic measures. Least-square error multiple linear regression models were developed for

Table I

R-Value, RMSE and NRMSE FOR PCI, FOS AND LR PREDICTIONS

Predicted Score ↓ Method →	R-Value			RMSE			Normalized RMSE (%)		
	PCI	FOS	LR	PCI	FOS	LR	PCI	FOS	LR
FIM-Motor-Intake	0.562	0.513	0.481	16.6**	17.0**	19.5	21.7	22.7	26.2
FIM-Total-Intake	0.566	0.596	0.450	17.4**	16.8**	20.6	21.2	20.5	25.2
FIM-Motor-Discharge	0.485	0.613	0.374	13.0**	11.8**	15.7	19.2	17.3	23.0
FIM-Total-Discharge	0.430	0.605	0.351	13.5**	12.5**	15.1	17.5	16.9	21.6
Length-of-Stay	0.371	0.447	0.218*	25.0**	23.7**	29.2	21.8	20.6	26.7
Purdue Pegboard	0.483	0.329	0.438	4.1**	4.5	4.3	14.1	15.7	14.6
Modified Ashworth Score	0.054*	0.041*	0.007*	0.405	0.420	0.431	31.2	29.6	32.3

* R-Values for which p-value is > 0.05.

** Significantly smaller average RMSE compared to LR column using t-test at 5% significance level.

prediction of a target clinical score value using robotic metrics as inputs. Optimal number of robotic metrics for inclusion in the model was determined by ranging the number of included metrics from 1 to the total number of metrics and choosing the optimal number based on the maximum R-value using a 10-fold cross validation analysis. The number of metrics which resulted in the highest R-value was subsequently chosen for each prediction. All evaluation for least-square LR analysis was performed in MATLAB.

The performance of the models were evaluated using three criteria:

R-Value: Performance of predictions for every clinical measure is reported as the *R* value between the actual and predicted scores over the entire patient population. *R* is a value between 0 and 1 and can be interpreted as the correlation coefficient between actual and predicted values and indicates the "goodness of fit", with an R value of 1 indicating a perfect fit.

Root-Mean-Square Error (RMSE): is a frequently used measure of model prediction performance. Formally, it represents the differences between values predicted by a model or an estimator and the actually measured values. For a sample of size *n*, predicted scores *ŷ(i)* and observed scores *y(i)*, *RMSE* is given by:

$$RMSE = \frac{\sqrt{\sum_{i=1}^{n}(y(i)-\hat{y}(i))^2}}{n} \qquad (7)$$

Normalized Root-Mean-Square Error (NRMSE): The normalized root-mean-square error (NRMSE) is the RMSE divided by the range (i.e. maximum – minimum) of observed values, *y*, of a predicted variable.

$$NRMSE = \frac{RMSE}{y_{max}-y_{min}} \qquad (8)$$

NRMSE is often expressed as a percentage, where lower values indicate less residual variance.

All models were evaluated by a 10-fold cross validation procedure using robotic metrics from 90% of the subjects to train the model with the remaining data from 10% of the subjects for model testing. This procedure was repeated 10 times, thereby using a previously untested 10% partition of the data in every round of the procedure. Overall model performance is the average of the performance of test data over the 10 folds. The same evaluation procedure was employed for all three methods: PCI, FOS, and LR. The entire process of 10-fold cross validation was repeated 100 times for FOS, PCI and LR to i) study the effect of parameters that change between different runs in PCI (i.e. the random selection of the first input to the model); and ii) to create a distribution of RMSE errors for all models.

III. Results

Table I shows the performance of PCI, FOS and LR using the three evaluation criterion above (R-value, RMSE and NRMSE). As can be observed, both system identification methods outperform LR for prediction of all clinical scores. The only exception is the *Purdue Pegboard* score for which LR outperforms FOS but not PCI. R-values indicated by * are those for which the associated p-value is > 0.05.

Comparison of both RMSE and Normalized RMSE columns for PCI, FOS, and LR in Table I also reflects the superior performance of both PCI and FOS over LR. To see if the error values are significantly different, we used the distribution of RMSE error. Error distributions for all predictions except the *Modified Ashworth Score* pass the Kolmogorov-Smirnov

normality test at *5%* significance level. A parametric t-test at *5%* significance level was then performed to test whether the means of the LR and either FOS or PCI error distributions are significantly different (pair-wise comparison of LR vs. FOS and LR vs. PCI). RMSE values marked by ** indicate a statistically significant smaller mean value.

IV. Discussion

As both R-value and RMSE results indicate, PCI performs better for *FIM-Motor-Intake* and *Purdue Pegboard* score predictions. For all prognosis-related predictions including *FIM-Motor-Discharge, FIM-Total-Discharge* and *Length-of-Stay*, FOS outperforms both PCI and LR. FOS also performs better for the prediction of *FIM-Total-Intake*, which is a diagnosis-related clinical score. (all RMSE distributions were tested using pair-wise t-test at 5% significance level).

Our results for prediction of the *Modified Ashworth Score* conform to the results obtained in [11]. This study also found a weak correlation value for this prediction using LR. Neither FOS nor PCI result in a significant correlation at the 5% significance level.

Overall, our results suggest suitability of non-linear system identification methods for prediction of diagnostic and prognostic scores. In particular, FOS shows superior performance for prediction of stroke prognosis.

An important advantage of FOS is its ability to identify the significant robotic metrics that contribute towards prediction of target functions. For the three prognosis-related predictions for which FOS performs better, our preliminary analysis of selected metrics indicates that the top robotic metrics picked by FOS belong to both visually-guided reaching and arm-position matching tasks. In particular, a metric associated with systematic shift ($Shift_{xy}$, i.e. related to proprioception) and one associated with initial movement error (Initial Movement Distance Ratio, i.e. related to sensorimotor performance) are the top two picks for prediction of *FIM-Motor-Discharge* and *FIM-Total-Discharge*. These findings are particularly significant since FIM is generally regarded as a motor dominant score. Yet, our results show that proprioceptive deficits are also an important predictor of a dominantly sensorimotor-related prognosis score.

PCI was used as a non-linear modeling approach in this study, whereby the clinical score-robotic metrics relationship was modeled based on correlation and polynomial fitting. PCI achieves better predictions for two diagnostic metrics. In particular, PCI performs better for prediction of *FIM-Motor-Intake.* A look at the top six preprocessed metrics that are used for this prediction reveals that, similar to FOS, metrics from both tasks are used for prediction of *FIM-Motor-Intake.* The top two correlation values correspond to a metric associated with initial movement distance ratio (i.e. related to sensorimotor performance) and a metric associated with variability (i.e. related to proprioception). This finding, together with the metrics identified by FOS, highlights the importance of proprioceptive function for the prediction of a predominantly motor-related score, i.e. FIM.

V. Conclusion

In this work, two methods known as PCI and FOS have been used to capture non-linear relationships between robot-based evaluation measures and stroke-related clinical scores. Experimental results show that both PCI and FOS are better predictors of stroke-related scores than a previously used method based on linear regression. In particular, our analysis indicates that FOS is well-suited for the prediction of prognosis-related scores. The superior performance of system identification methods is attributed to their ability to build non-linear models. PCI combines linear and static non-linear modeling to capture complex associations between robot-based metrics and stroke-related clinical scores while FOS searches through a large pool of non-linear candidate functions. FOS has the ability to identify the candidate functions that contribute towards function prediction. This has the potential to open new horizons for analysis of particular robotic metrics that predict stroke-related clinical scores .

References

[1] J. Adams, B. Bendixen, L. Kappelle, J. Biller, B. Love, D. Gordon, and d. Marsh, “Classification of subtype of acute ischemic stroke. Definitions for use in a multicenter clinical trial. TOAST. Trial of Org 10172 in Acute Stroke Treatment,” Stroke, vol. 24, no. 1, pp. 35–41, 1993.

[2] R. P. Donahue, R. D. Abbott, D. M. Reed, and K. Yano, “Alcohol and Hemorrhagic Stroke: The Honolulu Heart Program,” JAMA, vol. 255, no. 17, pp. 2311–2314, 1986.

[3] P. W. Duncan, L. B. Goldstein, R. D. Horner, P. B. Landsman, G. P. Samsa, and D. B. Matchar, “Similar motor recovery of upper and lower extremities after stroke”. Stroke, 25(6):1181-1188. 1994.

[4] D. T. Wade, R. Langton-Hewer, V. A. Wood, C. E. Skilbeck, and H.M. Ismail, “The emiplegic arm after stroke: measurement and recovery”. J. Neurol. Neurosurg. Psychiatry, 46(6):521-524. 1983.

[5] S.H. Scott and S.P. Dukelow. “Potential of robots as next-generation technology for clinical assessment of neurological disorders and upper-limb therapy”. J Rehabil Res Dev 2011;48(4):335–54.

[6] K. Ottenbacher, Y. Hsu, C. Granger, and R. Fiedler, “The reliability of the functional independence measure: a quantitative review,” Arch Phys Med Rehabil, vol. 77, no. 12, pp. 1226–1232, 1996.

[7] J. Gallus, and V. Mathiowetz, “Test-retest reliability of the Purdue pegboard for persons with multiple sclerosis”. American Journal of Occupational Therapy. 2003; 57(1):108-111.

[8] R.W. Bohannon, and M.B. Smith. “Inter-rater reliability of a modified Ashworth scale of muscle spasticity”. Physical Therapy. 1987; 67(2):206–207.

[9] A.M. Coderre, A.A. Zeid, S.P. Dukelow, M.J. Demmer, K.D. Moore, M.J. Demers, H. Bretzk, T.M. Herter, J.I. Glasgow, K.E. Norman, S.D. Bagg, S.H. Scott. “Assessment of upper-limb sensorimotor function of subacute stroke patients using visually guided reaching”. Neurorehabil Neural Repair. 2010; 24(6):528-41.

[10] S.H. Scott. “Apparatus for measuring and perturbing shoulder and elbow joint positions and torques during reaching”. J Neurosci Methods. 1999 Jul 15; 89(2):119-27.

[11] C. Bosecker, L. Dipietro, B. Volpe, H.I. Krebs. “Kinematic robot-based evaluation scales and clinical counterparts to measure upper limb motor performance in patients with chronic stroke”. Neurorehabil Neural Repair. 2010 Jan;24(1):62-9. Epub 2009 Aug 14.

[12] M.J. Korenberg. “Parallel cascade identification and kernel estimation for nonlinear systems,” Annals of Biomedical Engineering, vol. 19, no. 4, pp. 429–455, 1991.

[13] M.J. Korenberg. “A robust orthogonal algorithm for system identification”, Biological.Cybernetics. 1989; 60:267–276.

[14] M.J. Korenberg, L.D. Paarmann. “Orthogonal approaches to time–series analysis and system identification”. IEEE Signal Processing Magazine. 1991; 8(3):29–43.

[15] S.P. Dukelow, T.M. Herter, K.D. Moore, M.J. Demers, J.I. Glasgow, S.D. Bagg, K.E. Norman, S.H. Scott. “Quantitative assessment of limb position sense following stroke”. Neurorehabil. Neural Repair. 2010; 24(2):178-87.

[16] C. Gowland, P. Stratford, M. Ward, J. Moreland, W. Torresin, S. Van Hullenaar, J. Sanford, S. Barreca, B. Vanspall, N. Plews. “Measuring physical impairment and disability with the Chedoke-McMaster Stroke Assessment”. Stroke. 1993;24(1): 58–63.

[17] K. Singh, and S. H. Scott, "A motor learning strategy reflects neural circuitry for limb control", Nature Neuroscience, 6 (4):399-403, 2003.

[18] S. Dukelow, T.M. Herter, S.D. Bagg, S.H. Scott, “The independence of deficits in position sense and visually guided reaching following stroke”. J NeuroEngineering and Rehabilitation. 9:72, 2012.

[19] J. Hashemi, E. Morin, P. Mousavi, K. Mountjoy, and K. Hashtrudi-Zaad,. “EMG-Force modeling using parallel cascade identification”, J. Electromyogr. Kinesiol., 22: 469-477, 2012.