

# Differentiating Motor Coordination in Children with Cerebral Palsy and Typically Developing Populations Through Exploratory Factor Analysis of Robotic Assessments\*

Stephan C.D. Dobri, Dawa Samdup, Stephen H. Scott, T. Claire Davies, *Member, IEEE*

**Abstract**—General motor and executive functions are integral for tasks of daily living and are typically assessed when quantifying impairment of an individual. Robotic tasks offer highly repeatable and objective measures of motor and cognitive function. Additionally, robotic tasks and measures have been used successfully to quantify impairment of children with cerebral palsy (CP). Many robotic tasks include multiple performance parameters, so interpretation of results and identification of impairment can be difficult, especially when multiple tasks are completed. This study used exploratory factor analysis to investigate a potential set of quantitative models of motor and cognitive function in children, and compare performance of participants with CP to these models. The three calculated factors achieved strong differentiation between participants with mild CP and the typically developing population. This demonstrates the feasibility of these factors to quantify impairment and track improvements related to therapies.

**Clinical Relevance**— This establishes a method to differentiate atypical motor performance related to CP using a robotic reversed visually guided reaching task.

## I. INTRODUCTION

Effective motor function, such as point-to-point reaching, is an integral part of many acts of daily living. An increase in cognitive demands occurs as task complexity increases, for example, using a computer mouse which requires visuo-spatial processing instead of a touch screen. During assessments, it is important to test both motor processes and higher executive functions to quantify impairment.

Robotic assessments offer highly objective and repeatable assessments of motor function and cognition [1]. Different robotic platforms and tasks have been used extensively to measure impairment in function in adults with stroke and have been used to a lesser extent with children with CP [2-4]. Many robotic measures correlate well with established clinical measures of motor function, such as the Perdue Pegboard Test, and can differentiate well between typical and atypical performance [2, 4-13].

Cerebral palsy (CP) describes a group of permanent disorders of the development of posture and movement that are attributed to non-progressive disturbances to the developing fetal and infant brain [14]. The motor disorders of CP are often

accompanied by deficits in sensation, perception, and cognition [14]. Robotic devices have been used previously to assess different aspects of motor function in participants with CP [2, 4-13]. Most articles comparing participants with CP to those who are typically developing and compare the results of each performance parameter rather than creating normative or generalized models of motor function and cognition [4]. Robotic tests can include many different parameters, making interpretation of the results difficult relative to clinical tests with fewer parameters [15].

The goal of this research is to assess how exploratory factor analysis could be used to identify aspects of motor function of children with CP that differ from children who are typically developing. The study aimed to develop a set of factors to quantify impairment due to CP and simplify the interpretation of robotic assessments by reducing output parameters to clinically relevant factors. These factors could be used by clinicians and researchers to track the efficacy of different therapies for children with CP.

## II. METHODS

### A. Participants

Children who were typically developing were recruited from the Kingston, Ontario, Canada area. Two-hundred and eighty-eight participants (98 Female, 190 Male) between 5-18 years old (mean age: 12.9, SD: 3.2) participated.

Participants with CP were invited to participate by their physician. Three of the invited participants with CP volunteered. Diagnoses for all three participants were different. The 10-year-old male had a diagnosis of mild diplegia, the 11-year-old female had ataxic CP, and the 12-year-old male had hemiplegic CP. All three participants self-identified as being level 1 in the Manual Ability Classification System (MACS). The MACS level is a self-described level that describes how well a person can handle and manipulate objects with their hands [16]. A level of I indicates a person can “handle objects easily and successfully” [16].

All participants gave informed assent and informed consent was obtained from the guardians prior to participation. This study was approved by the Health Sciences and Affiliated Hospitals Research Ethics Board at Queen’s University, Kingston, Ontario, Canada (application number 6004951) in

\*Research supported by the Natural Sciences and Engineering Research Council under Grants 513272-17 and RGPIN-2016-04669, and by an Ontario Research Foundation – Research Excellence grant RE09-112. (Corresponding author: Stephan Dobri)

S. Dobri, D. Samdup, S. Scott, and T. Davies are with Queen’s University, Kingston, Ontario, Canada. 99 University Avenue, Kingston, Ontario,

Canada, K7K-3N6. (email: [stephan.dobri@queensu.ca](mailto:stephan.dobri@queensu.ca); [dawa.samdup@kingstonhsc.ca](mailto:dawa.samdup@kingstonhsc.ca); [claire.davies@queensu.ca](mailto:claire.davies@queensu.ca); [steve.scott@queensu.ca](mailto:steve.scott@queensu.ca)).

accordance with the Helsinki Declaration of 1975, as revised in 2000 and 2008.

### B. Robotic Apparatus and Task

Data were collected using the Kinarm Exoskeleton Lab (Kinarm, Kingston, Ontario, Canada). Participants sat in a system integrated chair with wheelchair-style seating, and their arms supported against gravity by the robot. They completed reaching tasks in a virtual environment in which their hands were obscured (they could not see the hand relative to the position of the targets). A modified point-to-point reaching task, reverse visually guided reaching (RVGR) assessed motor function and inhibition control. Participants were instructed to move a white dot into a red target as quickly and accurately as possible; however, the white dot moved opposite to the participant's hand (if the participant reached up and to the right, the dot moved down and to the left). Four targets were set in a square, 6 cm apart, with a fifth target at the centre. Each target was displayed six times in a pseudo-random order for a total of 24 reaches per arm. Reaches consisted of reaching out to the target, then back to the central target when it reappeared. The task is shown in Fig. 1. RVGR is a more cognitively demanding version of the task visually guided reaching which has been studied extensively in children with CP [4, 5, 17]. Both tasks use the same basic performance parameters to measure motor function; however, RVGR also records how long a participant takes to correct if they reach in the wrong direction.

The robot and performance parameters have been described in detail previously [15, 18, 19]. Significant learning effects across assessments on this task have been noted previously; however, within assessment learning effects have not been examined [20].

### C. Data Analysis

All data analyses were completed using MATLAB (TheMathWorks, Inc., Natick, MA, USA). An exploratory factor analysis (EFA) was completed to generate composite numeric scores from the performance parameters measured during the motor task using data from the typically developing participants. An EFA was computed rather than a principal component analysis (PCA) to allow for exploration of the theoretical structure of the data.

Sampling adequacy and sphericity of the data were tested to determine if the dataset was suitable for EFA. The sampling adequacy was tested using the Kaiser-Meyer-Olkin test and was found to be 0.82. Factor analyses are considered "meritorious" for values between 0.8 and 0.9 [21]. Bartlett's test for sphericity was used to assess the diagonality of the correlation matrix and the null hypothesis of diagonality was rejected ( $p < 0.001$ ). The results of these tests indicate the dataset was suitable for EFA.

Outlier data were removed using the same approach as Skarsgard et al. [5]. The interdecile range between the 10<sup>th</sup> and 90<sup>th</sup> percentiles was computed for each performance parameter, and any data beyond twice the interdecile range from the median value were identified as outliers and removed. If a participant's performance was an outlier in one performance parameter that test was removed and was not

assessed in any performance parameter. A total of 42 datapoints were removed (7% of collected data). After outliers were removed, each parameter was normalized to between [0,1] by dividing all parameters by their maximum recorded values. This normalization was necessary for all factor scores to be accurately calculated as different performance parameters had different magnitudes.

Two-, three-, and four-factor EFAs were conducted and compared. When factors were calculated, they were rotated using an oblique Procrustes rotation. An oblique rotation was chosen over an orthogonal rotation as oblique rotations allow for correlation between factors [22, 23]. Performance parameters that loaded on a factor with a magnitude of 0.5 or above were considered significant. Performance parameters that did not load significantly on any factor were excluded. The two-factor EFA was rejected as one of the two factors only had two significantly loaded variables. Typically, factors are only considered acceptable if they have at least three significantly loaded variables. The four-factor EFA was rejected as the fourth factor had only one significant loading. The three factors with significant loadings in the four-factor analysis were the same as found with the three-factor EFA, and the strength of the loadings was similar. A non-refined weighted sum was used to compute factor scores, as described by DiStefano et al. [24]. Performance parameters with loadings below 0.5 were excluded from the factor score.

Factor scores were calculated using the control group data and Gaussian distributions were fit to the factor scores. The factor scores and associated z-scores for each participant with CP were calculated to compare their performance to the typically developing population.

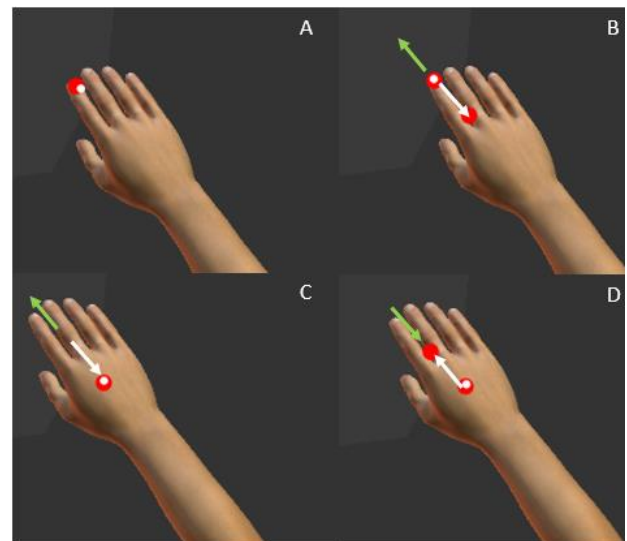


Figure 1: Schematic of the Kinarm RVGR task. Green arrows represent the direction the participant's hand moves and white represent the direction the white dot moves. A) shows the participant waiting at the central target for the next target to appear. B) shows a target appearing down and right from the central target. The participant must move their arm up and left (green arrow) to move the white dot to the target. C) shows when the participant has put the white dot in the red target. D) shows the central target reappearing, to which the participant must return to complete one reaching trial.

### III. RESULTS

The ten performance parameters included in the final EFA were reaction time (RT), initial direction angle (IDA), initial distance ratio (IDR), initial speed ratio (ISR), speed maxima count (SMC), max speed difference (MSD), movement time (MT), path length ratio (PLR), max speed (MS), and correction time (CT). The simplified three-factor models are below:

$F1$

$$= -0.63 * IDA + 0.93 * IDR + 0.97 * ISR - 0.64 * SMC$$

$$F2 = 0.88 * RT + 0.66 * MT + 0.71 * PLR + 0.52 * CT$$

$$F3 = 0.80 * MSD + 0.51 * PLR + 0.85 * MS$$

The first factor contains three performance parameters that directly quantify the initial movement of the reach, so was called Initial Movement (IM). Since this task involves reaction inhibition, it makes sense that the initial movement would be important for explaining variation in performance. It is not uncommon for participants to initially reach in the opposite direction to complete the task (reaching directly toward the target rather than directly away from it). The second factor contained measures of the overall speed, so was named the Speed of Movement (SM). The third factor contained measures of the directness of the path taken by the participant between the two points so was named the Directness of Movement (DM).

It should be noted that ideally performance parameters would only load significantly on one factor; however, one parameter has significant cross-loading. PLR loads significantly on both SM and DM; however, the magnitude of the cross-loading differs by 0.2, which is often considered the minimum acceptable difference for significant cross-loadings.

Fig. 2 shows the Gaussian distribution of each factor score, with z-scores bands and the factor scores for the participants with CP. The mean z-scores for all participants with CP were -6.22, 11.36, and 3.6 for IM, SM, and DM, respectively. All z-scores from participants with CP were beyond two, indicating all three factors can effectively differentiate performance of participants with CP from typically developing populations.

Previous performance measures with this patient population showed little differentiation between the participants with CP and normative models of typically developing performance, whereas this method showed strong differentiation [17]. The authors attributed the previous lack of differentiation to the mild impairment indicated by the participants' MACS and GMFCS levels. The previous research used a simple point-to-point reaching task, so the increased differentiation may be related to increased task difficulty. The factor analysis may be a more sensitive tool to impairments than individual parameter analysis. This sensitivity may make the factor analysis a good tool for tracking and assessing the efficacy of therapies for participants with CP.

It is important to note that this is a proof of concept since the group of participants with CP in this study is too small to draw meaningful conclusions. While the results are promising, a much larger cohort of participants with CP will need to be tested. Future work will involve collecting and testing a larger cohort of participants with CP. Collection of a larger cohort had been intended for this work; however, restrictions due to COVID-19 stopped data collection.

The three participants with CP had different etiologies and topographical involvement. Previous work has shown that there are significant differences in performance of robotic reaching tasks among participants with the same diagnosis and topographical involvement based on how the brain was affected during development [7-10, 12, 13]. Future work should make group comparisons based on diagnosis and topographical involvement.

### IV. CONCLUSION

Exploratory factor analysis (EFA) was conducted to establish composite scores of performance of typically developing children on a modified robotic reaching task. The factor scores were used to differentiate performance of three participants with cerebral palsy (CP). A three-factor model was selected where the individual factors reflected the initial

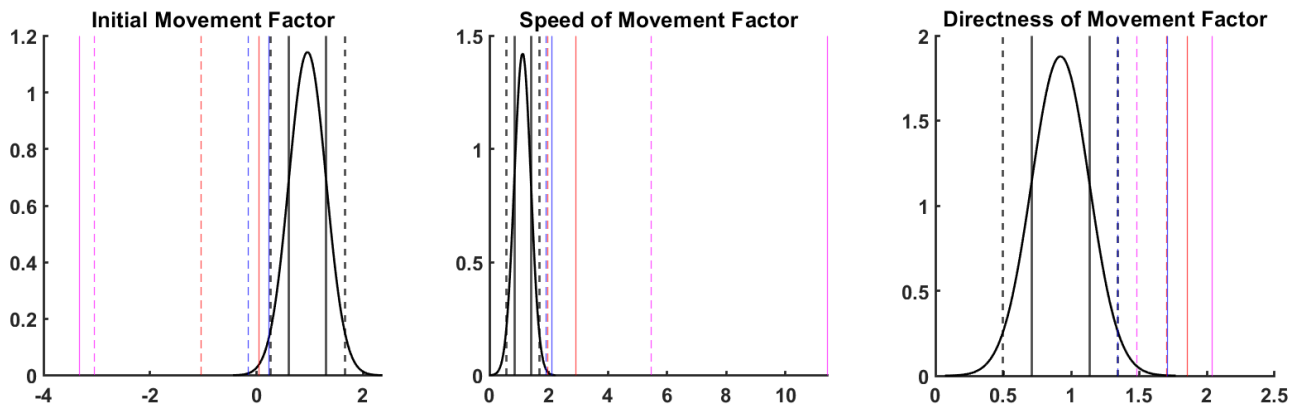


Figure 2: Gaussian distribution of factor scores from the typically developing datasets and factor scores from the participants with CP. The solid black lines represent one standard deviation from the mean (a z-score of one), and the dotted black lines represent two standard deviations from the mean (a z-score of 2). The coloured lines represent the performance of participants with CP, with the dashed lines representing affected/non-dominant arms and the solid line the unaffected/dominant arm. The red, blue, and magenta lines are for the 12-year-old, 10-year-old, and 11-year-old, respectively.



movement, speed of movement, and directness of movement. All three factors differentiated performance of participants with CP from typically developing participants; all z-scores of participants with CP were beyond two. Future work will include collecting more participants with CP to evaluate the efficacy of the factors at differentiating typical and impaired performance.

#### ACKNOWLEDGMENT

The authors would like to thank: S. Appaqaq, H. Bretzke, E. Heming, and K. Moore, for their technical support; and E. Aleska, E. Castillo, J. Empey, A. Gowthorpe, E. Hoskin, L. Jansen, E. Johannessen, S. Klinger, A. Lax-Vanek, A. Lopez, L. Munro, E. Neff, E. Perfect, E. Rendall, O. Roud, N. Smith, R. Spender, and K. Van-Til for their help with data collection.

#### CONFLICT OF INTEREST

S.H. Scott is the co-founder and Chief Scientific Officer of Kinarm, the company which develops and commercializes the robot and task used in this study.

#### REFERENCES

- [1] C. E. Little *et al.*, "Test-retest reliability of KINARM robot sensorimotor and cognitive assessment: in pediatric ice hockey players," *Journal of neuroengineering and rehabilitation*, vol. 12, p. 78, 2015, doi: [10.1186/s12984-015-0070-0](https://doi.org/10.1186/s12984-015-0070-0).
- [2] Y.-P. Chen and A. M. Howard, "Effects of robotic therapy on upper-extremity function in children with cerebral palsy: A systematic review," *Developmental Neurorehabilitation*, vol. 19, pp. 64-71, 2016, doi: [10.3109/17518423.2014.899648](https://doi.org/10.3109/17518423.2014.899648).
- [3] M. Sivan, R. O'Connor, S. Makower, M. Levesley, and B. Bhakta, "Systematic review of outcome measures used in the evaluation of robot-assisted upper limb exercise in stroke," *Journal of rehabilitation medicine*, vol. 43, pp. 181-189, 2011, doi: [10.2340/16501977-0674](https://doi.org/10.2340/16501977-0674).
- [4] S. C. Dobri, H. M. Ready, and T. C. Davies, "Tools and Techniques Used With Robotic Devices to Quantify Upper-Limb Function in Typically Developing Children: A Systematic Review," *Rehabilitation Process and Outcome*, vol. 9, p. 1179572720979013, 2020, doi: [10.1177/1179572720979013](https://doi.org/10.1177/1179572720979013).
- [5] M. Skarsgard, S. C. D. Dobri, D. Samdup, S. H. Scott, and T. C. Davies, "Toward Robot-Assisted Diagnosis of Developmental Coordination Disorder," *IEEE Robotics and Automation Letters*, vol. 4, no. 2, pp. 346-350, 2019, doi: [10.1109/lra.2018.2885197](https://doi.org/10.1109/lra.2018.2885197).
- [6] M. Germanotta *et al.*, "Robotic and clinical evaluation of upper limb motor performance in patients with Friedreich's Ataxia: an observational study," (in English), *J Neuroengineering Rehabil*, vol. 12, p. 41, Apr 23 2015, doi: <https://doi.org/10.1186/s12984-015-0032-6>.
- [7] A. M. Kuczynski, A. Kirton, J. A. Semrau, and S. P. Dukelow, "Bilateral reaching deficits after unilateral perinatal ischemic stroke: a population-based case-control study," (in English), *J Neuroengineering Rehabil*, Journal Article vol. 15, no. 1, p. 77, Aug 17 2018, doi: <https://doi.org/10.1186/s12984-018-0420-9>.
- [8] A. M. Kuczynski *et al.*, "Corticospinal tract diffusion properties and robotic visually guided reaching in children with hemiparetic cerebral palsy," (in English), *Human Brain Mapping*, Article vol. 39, no. 3, pp. 1130-1144, Mar 2018, doi: [10.1002/hbm.23904](https://doi.org/10.1002/hbm.23904).
- [9] A. M. Kuczynski, J. A. Semrau, A. Kirton, and S. P. Dukelow, "Kinesthetic deficits after perinatal stroke: robotic measurement in hemiparetic children," (in English), *J Neuroengineering Rehabil*, Journal Article vol. 14, no. 1, p. 13, 02 15 2017, doi: <https://doi.org/10.1186/s12984-017-0221-6>.
- [10] A. M. Kuczynski, S. P. Dukelow, J. A. Semrau, and A. Kirton, "Robotic quantification of position sense in children with perinatal stroke," (in English), *Neurorehabilitation and neural repair*, vol. 30, no. 8, pp. 762-772, 01 Sep 2016, doi: [http://dx.doi.org/10.1177/1545968315624781](https://doi.org/10.1177/1545968315624781).
- [11] A. M. Kuczynski *et al.*, "Sensory Tractography and Robot-Quantified Proprioception in Hemiparetic Children with Perinatal Stroke," (in English), *Human Brain Mapping*, Article vol. 38, no. 5, pp. 2424-2440, May 2017, doi: [10.1002/hbm.23530](https://doi.org/10.1002/hbm.23530).
- [12] R. L. Hawe, A. M. Kuczynski, A. Kirton, and S. P. Dukelow, "Assessment of bilateral motor skills and visuospatial attention in children with perinatal stroke using a robotic object hitting task," (in English), *Journal of neuroengineering and rehabilitation*, vol. 17, no. 1, p. 18, 2020, doi: [http://dx.doi.org/10.1186/s12984-020-0654-1](https://doi.org/10.1186/s12984-020-0654-1).
- [13] R. L. Hawe, A. M. Kuczynski, A. Kirton, and S. P. Dukelow, "Robotic assessment of rapid motor decision making in children with perinatal stroke," (in English), *Journal of neuroengineering and rehabilitation*, vol. 17, no. 1, p. 94, 2020, doi: [http://dx.doi.org/10.1186/s12984-020-00714-1](https://doi.org/10.1186/s12984-020-00714-1).
- [14] P. Baxter *et al.*, "The definition and classification of cerebral palsy," *Dev Med Child Neurol*, vol. 49, no. s109, pp. 1-44, 2007.
- [15] M. D. Wood, L. E. R. Simmatis, J. Gordon Boyd, S. H. Scott, and J. A. Jacobson, "Using principal component analysis to reduce complex datasets produced by robotic technology in healthy participants," *Journal of neuroengineering and rehabilitation*, vol. 15, no. 1, p. 71, 2018/07/31 2018, doi: [10.1186/s12984-018-0416-5](https://doi.org/10.1186/s12984-018-0416-5).
- [16] A.-C. Eliasson *et al.*, "The Manual Ability Classification System (MACS) for children with cerebral palsy: scale development and evidence of validity and reliability," *Developmental Medicine & Child Neurology*, vol. 48, no. 7, pp. 549-554, 2006, doi: [10.1017/S0012162206001162](https://doi.org/10.1017/S0012162206001162).
- [17] S. C. D. Dobri, D. Samdup, S. H. Scott, and T. C. Davies, "Differentiating Motor Coordination and Position Sense in Children with Cerebral Palsy and Typically Developing Populations Through Robotic Assessments\*," in *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, 20-24 July 2020 2020, pp. 3654-3657, doi: [10.1109/EMBC44109.2020.9175878](https://doi.org/10.1109/EMBC44109.2020.9175878).
- [18] S. H. Scott, "Method and apparatus for assessing or detecting brain injury and neurological disorders," 2012.
- [19] A. M. Coderre *et al.*, "Assessment of Upper-Limb Sensorimotor Function of Subacute Stroke Patients Using Visually Guided Reaching," *Neurorehabilitation and neural repair*, vol. 24, pp. 528-541, 2010, doi: [10.1177/1545968309356091](https://doi.org/10.1177/1545968309356091).
- [20] L. E. R. Simmatis, S. Early, K. D. Moore, S. Appaqaq, and S. H. Scott, "Statistical measures of motor, sensory and cognitive performance across repeated robot-based testing," *Journal of neuroengineering and rehabilitation*, vol. 17, no. 1, p. 86, 2020/07/02 2020, doi: [10.1186/s12984-020-00713-2](https://doi.org/10.1186/s12984-020-00713-2).
- [21] H. F. Kaiser, "An index of factorial simplicity," *Psychometrika*, vol. 39, no. 1, pp. 31-36, 1974/03/01 1974, doi: [10.1007/BF02291575](https://doi.org/10.1007/BF02291575).
- [22] T. A. Schmitt and D. A. Sass, "Rotation Criteria and Hypothesis Testing for Exploratory Factor Analysis: Implications for Factor Pattern Loadings and Interfactor Correlations," *Educational and Psychological Measurement*, vol. 71, no. 1, pp. 95-113, 2011/02/01 2011, doi: [10.1177/0013164410387348](https://doi.org/10.1177/0013164410387348).
- [23] E. Ferguson and T. Cox, "Exploratory Factor Analysis: A Users' Guide," *International Journal of Selection and Assessment*, <https://doi.org/10.1111/j.1468-2389.1993.tb00092.x> vol. 1, no. 2, pp. 84-94, 1993/04/01 1993, doi: <https://doi.org/10.1111/j.1468-2389.1993.tb00092.x>.
- [24] C. DiStefano, M. Zhu, and D. Mindrila, "Understanding and using factor scores: considerations for the applied researcher," *Practical Assessment, Research, and Evaluation*, vol. 14, no. 20, pp. 1-11, 2009, doi: <https://doi.org/10.7275/da8t-4g52>.