Data Sample Size Needed for Analysis of Kinematic and Muscle Synergies in Healthy and Stroke Populations

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***Abstract*— Multiple studies have suggested the central nervous system (CNS) generates motions by using modular control of muscles and joints (synergies). However, the synergies reported by these studies are task dependent and might not reflect the true control strategies adopted by the CNS. Studying exploratory motions (EMs) can reveal biomechanical constraints and motor control strategies in healthy and clinical populations. The first logical step to consider EMs in study of motor synergies is to determine how much data is required to reliably and fully profile the motion patterns of an individual. Here we present how the quality of motor synergies analysis depends on the amount of EM data included in the analysis. We recruited 10 healthy and 10 post-stroke participants and collected electromyography (EMG) and joint motion data of their arms as they completed a motor exploration task. We compared the effects of clinical status and limb strength/dominance on the amount of data required to identify synergies. Clinical status had a significant effect on the required amount of data for both datasets. Limb strength had a significant effect only for kinematic data. We determined the upper bound 95% confidence interval to set the amount of data required for synergy analysis in both populations: 235 sec for EMG data and 265 sec for kinematic data. Our results provide an important step toward using motor exploration in the study of healthy motor synergies and how stroke alters them.**

I. Introduction

The control of upper-body reaching motions is a complex task for the central nervous system (CNS), as the dynamic relationships between activation of muscles, joint torques, and joint motions are non-linear and time-dependent. The redundancy in the human musculoskeletal system also adds to the complexity of this task. An extensive set of experimental evidence suggests that the CNS coordinates the muscular and kinematic elements of motion using modular control of muscle activations or joint motions [1]–[7].

Motor synergies (i.e., muscle or kinematic synergies) are the underlying concept of the suggested modular control of motions. The CNS may generate motor commands through a linear combination of motor synergies, each controlling a group of muscles or joints (elemental variables) [8]. Such co-activation of elemental variables leads to a reduction in the dimensionality of the motor control task. To quantify motor synergies, dimensionality reduction methods [9] are available to analyse large sets of muscle activity (electromyography) data or joint angle changes observed over the course of motor tasks.

Study of motor synergies in the stroke survivor population can provide additional insights to complement clinical assessments such as the Fugl-Meyer and Wolf Motor Function. The recovery of upper-limb function following stroke is characterized by the emergence of abnormal movement coordination and patterns. These patterns can be quantified as altered motor synergies. Clinical assessments used by therapists are focused on the ability to perform different activities (i.e., functional assessments). However, analysis of motor synergies can offer an insight into what is causing the inability to complete functional tasks. Motor synergy characterization can complement functional assessments and provide an opportunity to formulate individualized exercises that focus on the roots of the motor impairment of each patient [10].

A main critique of motor synergies studies is that the synergies they report are task-specific and might be reflecting the biomechanical constraints of the task rather than the underlying neural strategies of motor control [11]–[14]. In our previous work, we proposed a setup to quantify motor synergies demonstrated during *exploratory motor tasks* instead of goal-directed motor tasks with physical constraints [15]. The way humans execute an exploratory task is a function of their own biomechanical constraints [16] and motor control strategies. Therefore, analyzing the motion patterns of an individual during an exploratory task has the potential to reveal individualized motion tendencies or motor deficits [17]–[19].

An important initial step is to systematically determine the duration of data required to fully capture the motion patterns of an individual. It is possible that each person may require a different amount of data to be fully profiled. In this paper we will explore whether a fairly consistent amount of data can reliably quantify motor synergies of any person. We will also study the effects of clinical status (stroke vs. healthy), type of data (muscle activation vs. joint motion), and limb strength (limb dominance for the healthy population, stroke-affected vs. less-affected limb for the clinical population) on the required data sample size.

In Section II of this paper we provide the details of our experimental and analytical methods. Section III covers results, Section IV discusses the results and concludes by reflecting on the findings of this work.

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II. METHODS

A. Research Ethics and Study Participants

This study was approved by University of British Columbia's Clinical Research Ethics Board. Ten healthy adults and ten stroke survivors were recruited and provided written consent to take part in this study.

The average age was 24.3 years for the healthy participants and 60.5 years for the stroke survivors, with a standard deviation of 3.3 and 9.9 years, respectively. The male to female ratio was 7/3 for both participant groups. All stroke survivor participants had a moderate impairment as measured by the upper-extremity Fugl-Meyer (FM) scale (range of FM scores between 21 to 50 is considered moderate impairment [20]). Subjects had an average score of 37.2 with a standard deviation of 9.5.

B. Experiment Setup and Protocol

This study employed the same experimental setup as our previous studies [15], [21], [22]. We used a system that utilizes skeleton data read from a Microsoft Kinect® to map the user's bilateral hand motions to the motion of a cursor on a computer screen. In order to control the cursor's motion, the user was required to move both hands at the same time in the same direction. The participant then played a simple video game using cursor motion.

Each participant took part in one data collection session. After becoming familiar with the system and controlling the computer cursor with their hand motions, participants were introduced to the game called "Lucky Pirate" (OUAT Entertainment). This game provides a virtual reality based motor exploration task [19] set on a static background and requires players to explore the entire game screen to select and click on treasure chests that may contain gold coins. Completion of a level does not carry a time restriction; as a result, users are able to progress at their own pace.

The participants were asked to play the game for five periods, with each period covering three minutes of gameplay. During each gameplay period, joint motion data and EMG data were collected. We used a Microsoft Kinect V1 to record joint angles of the following upper limb joints: shoulders (6 DOF), elbows (4 DOF), wrists (4 DOF), and trunk rotations (3 DOF). A 16-channel Delsys EMG system was used to record muscle activation from 8 muscles on each side of the body: the brachioradialis, biceps brachii, triceps brachii (long and lateral heads), deltoid (anterior, medial, and posterior fibers), and pectoralis major (clavicular fibres) [23]–[26]. EMG electrodes were placed in accordance with the European recommendations for surface electromyography [27].

C. Data Preprocessing

Before extracting muscle synergies, the EMG signals were amplified (×1000) and band-pass filtered (20-450 Hz) [25], [28]. Each muscle's EMG signals were normalized to the maximum observed value of the signal. The preprocessed EMG data for each participant were then stored in two files, the dominant and non-dominant limb for healthy participants and the stroke-affected and less-affected limbs for the stroke survivors, each including data from 8 muscles.

The Microsoft Kinect motion capture system was used to collect joint kinematics data [29], [30]. The Kinect tracked the Cartesian locations of several anatomical landmarks by assigning markers to them: centre of hip, chest at the level of shoulders, shoulders, elbows, wrists, and hands (i.e., centre of palms).

To calculate joint angles from marker positions, a human upper-body musculoskeletal model developed by Holzbaur [31] for the OpenSim environment [32] was used. The original model only includes the right extremity. This model was modified and expanded to include both extremities and to be compatible with Kinect data. Using OpenSim software and the modified musculoskeletal model, the inverse kinematics of the marker motions were solved to find the change in the following joint angles over time: Trunk motions as measured by roll, pitch, and yaw angles, flexion-extension of both shoulders, abduction-adduction of both shoulders, medio-lateral rotation of both shoulders, flexion-extension of both elbows, pronation-supination of both elbows, radial-ulnar deviation of both wrists, flexion-extension of both wrists (17 DOFs).

Using this procedure, the joint angle time series during a motor exploration task for all participants were calculated at 30 Hz. These data were then bifurcated with each set containing the joint angle time series data of the dominant/non-dominant or affected/less-affected upper limbs of each participant (10 DOFs in each set; trunk motion data was shared). Only movements within two standard deviations of the mean speed of the entire session were kept for further analysis. This was to ensure that all periods of pause or no movement were filtered out. The joint motion data were low-pass filtered at 6 Hz [19], [33] to remove motion artefacts.

D. Quantifying Motor Synergies

Synergy analysis of kinematics and EMG data was performed independently for each limb (i.e., within arm synergies, not between arm synergies). Following the common formulation in the literature [8], [25], [34], [35], a $t \times m$ matrix $\mathbf{M}$ containing the time-series of change in m motion effectors (muscle EMGs or joint angles) can be measured (t is the number of data points). A matrix factorization method (Non-negative Matrix Factorization (NNMF) for this study) will solve for a set of n synergy vectors w ($1 \times m$ dimensional) arranged in an $n \times m$ synergy structure matrix $\mathbf{W}$ ($n < m$). Each synergy vector specifies a relative mode of activation/use of the motion effectors during the task. This synergy structure is found so that the error in reconstructing the motion elements in matrix $\mathbf{M}$ using a linear combination of the synergy vectors is minimized. This linear combination of the synergy vectors is expressed as $\mathbf{M} = \mathbf{C} \times \mathbf{W} + \mathbf{E}$, where $\mathbf{C}$ is a $t \times n$ activation matrix and $\mathbf{E}$ is the unexplained variation.

The collected data were divided to muscle and kinematic sets, each set containing separate time series data for the two limbs. Variance Accounted For (VAF) was used to determine the number of synergy vectors ensuring sufficient factorization of the data by NNMF method [15]. The number of synergy vectors is the minimum number of synergies that achieves a global (across all training data points) VAF > 90%, with less than a 5% increase in global VAF upon addition of another synergy vector. As a local criterion, the VAF for each muscle or joint (DOF VAF) is required to exceed 50%. This procedure

ensures that the estimated number of synergies could predict both the overall data set as well as each of the DOFs of the overall data set.

E. Data Analysis

The collected data were divided to muscle and kinematic sets, each set containing separate time series data for the strong and weak limbs (dominant and non-dominant for healthy participants, stroke-affected and less-affected for stroke survivors).

To obtain a view of how movement patterns changed throughout motor exploration practice, we quantified motor synergies of movement data cumulated over time. We divided subject motor exploration datasets into 5 sec epochs. Starting with considering one epoch and then adding one more epoch in each step, we studied how adding more data changes the quantified synergies.

In each step we chose x epochs randomly (x changes between 1 to the maximum number of available epochs for each participant). Then we randomly assigned 50% of the data within each epoch into a training set and the other 50% to a validation set. This was followed by combining all x of the training and validation sets into one training set and one validation set. We quantified the synergy vectors of the training set and the validation set. To quantify how parallel two vectors are, the dot product of the two vectors can be used. Therefore, the dot product is a way to quantify the similarity in the synergy *structure* by identifying the shared (i.e., parallel) vectors of the two data sets [2]. We matched the synergy vectors of the training and validation sets to find the combination that produces the highest total sum of dot products. The total sum of dot products divided by the number of identified synergies in the training set was used as a metric to calculate the similarity of the identified synergy sets. This procedure was repeated 45 times for each x (a 45-fold resampling). The mean of the similarity scores generated for the 45 repetitions was used as a measure for the quality of synergy characterization.

These calculations were done for all participants (strong and weak limbs were considered separately; the participants were grouped by population). By adding more epochs to the analysis, the quality of synergy characterization gets progressively closer to one. Fig. 1 shows how quality of synergy characterization changed as more epochs were included for the EMG data of the strong limb of stroke participant #8 (blue dots). This indicates that the synergy vectors of the training sets and the validation sets become more and more parallel and thus, similar. We define the time to characterization (i.e., the amount of data needed to fully capture the motion patterns of an individual) as the time in which the quality of synergy characterization plateaus.

To determine the time to characterization, we fitted a function (1) to calculate the quality of synergy characterization data needed for each case.

$$y = a \times e^{-x/b} - c / x + d \qquad (1)$$

In (1), y is the quality of synergy characterization and x is the epoch number. As the number of epochs x increases, y approaches the asymptote value d. We consider the time to reach 95% of this value as the time to characterization.

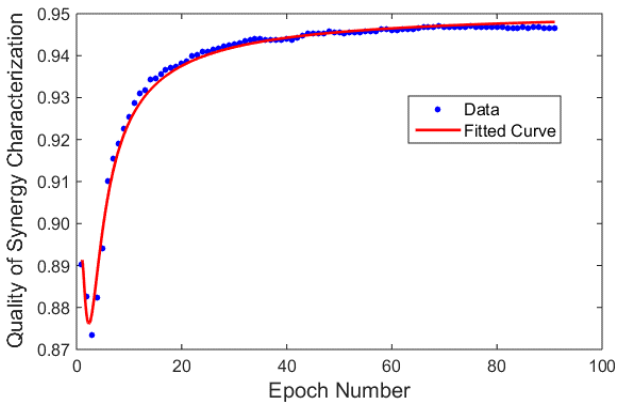

Figure 1. Quality of synergy characterization changes as more epochs are included in the analysis. Blue dots show the calculated quality measure for the strong limb's EMG data of stroke participant #8. The red line is the curve fitted to the blue dots. Each epoch includes 5 sec of data.

With this procedure, we calculated the time to characterization for the two limbs of each participant in the two population groups. This was done separately for the kinematic and EMG datasets. For each of these data sets, we compared the time to characterization between the two limbs and the two populations using a 2×2 Analysis of Variance, with population (2 levels) and limb strength (2 levels) as factors. Differences with a probability of less than 0.05 (adjusted with Bonferroni's correction for multiple comparisons) were considered significant.

III. Results

For each participant's motor exploration datasets, we quantified how characterization of motor synergies evolved over cumulative epochs. This was done using a 45-fold resampling technique to generate training and validation datasets to study the effects of arm strength and clinical status on the amount of data required to reliably profile an individual's kinematic and muscle synergies.

Increasing the amount of data included in motor synergy analysis gradually increased the quality of synergy characterization. Fig. 2 shows this general trend for all participants (lines on the graphs) divided by the data type (EMG on top row and kinematic data on the bottom), and clinical status and arm strength (columns). This trend indicates synergy vectors extracted from the training and validation datasets became more similar with the addition of more data, suggesting a more reliable synergy extraction.

This trend in the quality of synergy characterization was used to calculate the time to characterization for each of the 4 conditions (columns of Fig. 2) on the two datasets (rows of Fig. 2). For each data type we performed a repeated–measures 2×2 ANOVA (arm strength and clinical status as the two factors, each having two levels at n = 10). There was no statistically significant interaction between arm strength and clinical status. Tables 1 and 2 show a summary of how the time to characterization vary between the mentioned conditions.

On average, more data was required to characterize both muscle and kinematic synergies of the stroke survivors compared to healthy adults. However, the strength of the limb (hand dominance for healthy adults and side less affected by

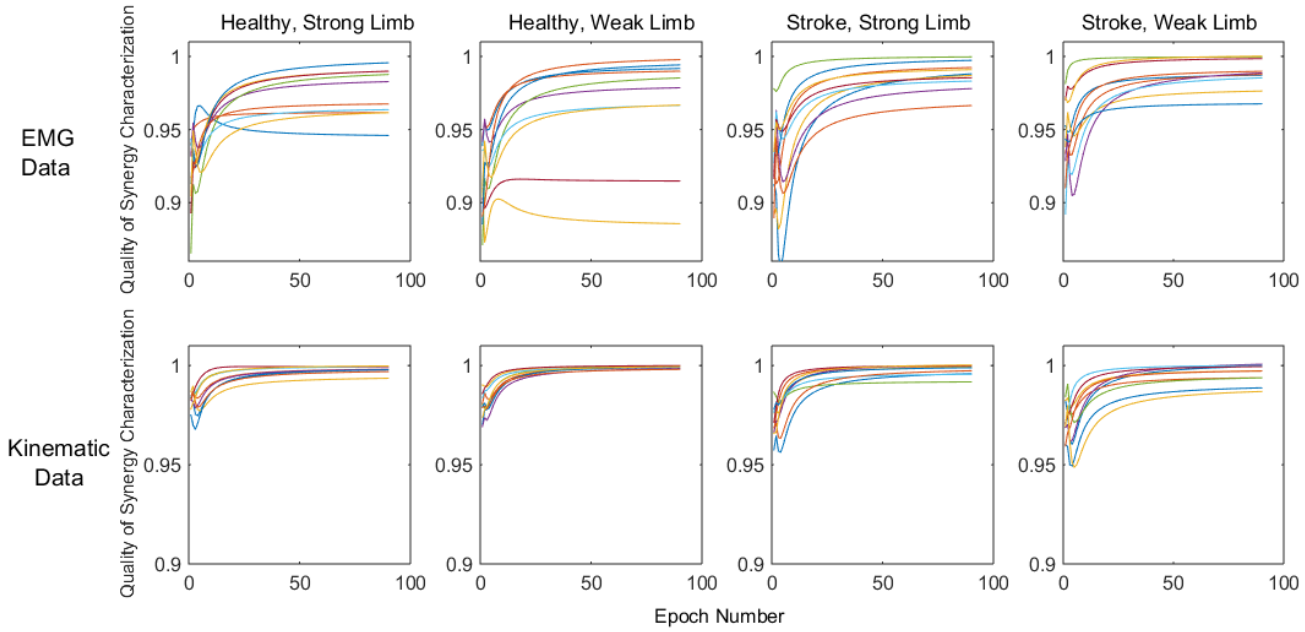

Figure 2. Increasing the amount of data included in motor synergy analysis gradually increased the quality of synergy characterization. This trend is shown for all 10 participants (lines on the graphs) divided by the data type (EMG on top row and kinematic data on the bottom), and clinical status and arm strength (columns).

stroke for the clinical group) had different effects on the time to characterization depending on data type.

Considering muscle synergies, clinical status of the individuals had a statistically significant effect on the time to characterization (healthy adults 40.6 epochs and stroke survivors 46.3 epochs, $p < 0.05$). Arm strength did not have a significant effect on time to characterization.

Both arm strength and clinical status had a statistically significant effect on time to characterization of kinematic synergies. Significantly more epochs ($p < 0.01$) were required to reliably quantify kinematic synergies of the stroke survivors (45.5 epochs) compared to the healthy adults (38.3 epochs). Similarly, significantly more epochs ($p < 0.05$) were required to quantify the kinematic synergies of the weak arm (44.8 epochs) compared to the strong arm (39.0 epochs) of the participants.

Based on the samples analysed in this study, we built 95% confidence intervals (CI) of time-to-synergy characterization. The upper bound of these CIs can be treated as the minimum amount of data required to reliably quantify motor synergies. The upper bound of the time-to-characterization CIs for the stroke survivors was higher than for the healthy participants for both muscle synergies (52.8 epochs vs. 46.1 epochs) and kinematic synergies (53.1 epochs vs. 47.6 epochs).

TABLE I. TIME TO CHARACTERIZATION OF MUSCLE SYNERGIES IN NUMBER OF EPOCHS. EACH EPOCH INCLUDES 5S OF EMG DATA.

	Healthy Adults	***Stroke Survivors***
Strong Arm	40.5 ± 6.6	47.5 ± 8.3
Weak Arm	40.8 ± 8.1	45.2 ± 9.8

TABLE II. TIME TO CHARACTERIZATION OF KINEMATIC SYNERGIES IN NUMBER OF EPOCHS. EACH EPOCH INCLUDES 5S OF USING JOINT MOTION DATA.

	Healthy Adults	***Stroke Survivors***
Strong Arm	35.3 ± 8.2	42.8 ± 9.3
Weak Arm	41.3 ± 4.6	48.2 ± 7.41

IV. DISCUSSION AND CONCLUSION

In order to use motor exploration in the study of motor synergies, it is necessary to determine the amount of data required to fully capture the motion patterns of healthy and stroke-survivor individuals. We used a statistical approach to build a model of how the outcome of motor synergy analysis becomes more complete and reliable as more data are included in the analysis.

There was no significant effect observed when time-to-characterization of muscle synergies was compared between the two limbs. However, the difference was significant between the two limbs when considering kinematic synergies. Moreover, our results illustrate that more data are required to quantify both muscle and kinematic synergies of the stroke population compared to healthy adults. Post-stroke motor deficits cause changes in patterns of movement, making them generally more spastic and slower. We believe this changes the quality and richness of the electromyography and joint motion data that were collected during the study from the stroke survivors. It is interesting to study if a stroke-survivor's Fugl-Meyer score is correlated with the calculated time to characterization. In that case, the difference between time to characterization between the healthy and clinical population can be used as a way to track the improvement of the stroke-survivors as they complete their physical therapy regimens.

To answer how much data are required to fully capture the motion patterns of an individual for motor synergy analysis, we built 95% confidence intervals (CI) of time-to-synergy characterization. The upper bound of the CI for the stroke

survivors was 53 epochs, and 47 epochs for the healthy adults. This means that to study post-stroke muscle or kinematic synergies, at least 53 × 5 = 265 sec of "active" motor exploration data are required to be able to reliably profile a stroke survivor's motion patterns. This number is 47 × 5 = 235 sec for healthy adult participants. Here we consider preprocessed data (see section "C. Data Preprocessing" under Methods) as active motor exploration data.

To the best of our knowledge, this study is the only one that has considered the relationship between the quality of motor synergy analysis and the size of data included in the analysis. The common practice in the field of motor synergies is to collect data during multiple repetitions of a simple task like reaching between two specific points or walking on a treadmill. As these tasks are cyclic or biomechanically constrained, the motion data is highly repeatable for each individual. Therefore, a reliable and complete motion dataset can be collected by simply sampling from multiple trials of the task. However, in an exploratory reaching motion task, by removing the biomechanical constraints imposed by reaching between two points, the collected data will not be repeatable from one trial to another. This makes it a necessity to determine how much data is needed to identify motor synergies from exploratory motions. The methods presented in this paper are close to those used by Wright et al. in [36] to study how much table-top exploratory reaching motion data is required to study movement (position, velocity, acceleration) distributions in healthy and stroke populations.

As the use of sensors to collect data about different aspects of motion in different clinical populations becomes more mainstream, it becomes easier to build statistical models of motor behaviour as a way to assess motor deficits. The work we present here is a first step toward generating procedures to remove bias in collection of motion data for building such statistical models. We believe collecting "enough" motor exploration data to analyze motor synergies post-stroke can lead to better understanding of how stroke causes motor deficits in each person. This in turn can be used to design data-driven and individualized physical therapy exercises.

Building on the work presented in this paper, in our future studies, we aim to investigate human upper body motor coordination to demonstrate the viability of synergistic motor control theory in describing the natural upper body movements, as well as quantifying the effects of stroke on motion generation. This work will be expanded to also investigate the process of motor recovery after stroke by describing how motor synergies change as stroke-survivors complete a conventional physical therapy regimen. This findings from these studies can be used in quantifying motor deficits, fulfilling the need for objective clinical assessments [37], [38]. Moreover, these studies can inform the design of individualized care for physical therapy clients by using motor synergies as performance metrics in developing therapy tools that increase engagement of therapy clients in their exercise (similar to our previous works [39]-[42]).

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REFERENCES

[1] P. Azaripasand, A. Maleki, and A. Fallah, "The extraction of time-varying muscle synergies during hand-reaching movement with a K-means assisted approach," in *23rd Iranian Conference on Electrical Engineering (ICEE 2015)*, 2015, pp. 84–87.

[2] G. Torres-Oviedo and L. H. Ting, "Subject-specific muscle synergies in human balance control are consistent across different biomechanical contexts.," *J. Neurophysiol.*, vol. 103, no. 6, pp. 3084–3098, 2010.

[3] M. Tagliabue, A. L. Ciancio, T. Brochier, S. Eskiizmirliler, and M. A. Maier, "Differences between kinematic synergies and muscle synergies during two-digit grasping," *Front. Hum. Neurosci.*, vol. 9, no. March, pp. 1–17, 2015.

[4] R. Vinjamuri, V. Patel, M. Powell, Z. Mao, and N. Crone, "Candidates for synergies : linear discriminants versus principal components," *Comput. Intell. Neurosci.*, vol. 2014, pp. 1–10, 2014.

[5] S. Hagio, M. Fukuda, and M. Kouzaki, "Identification of muscle synergies associated with gait transition in humans," *Front. Hum. Neurosci.*, vol. 9, no. 48, pp. 1–12, 2015.

[6] P. Braido and X. Zhang, "Quantitative analysis of finger motion coordination in hand manipulative and gestic acts," *Hum. Mov. Sci.*, vol. 22, no. 6, pp. 661–678, 2004.

[7] J. F. Soechting and M. Flanders, "Flexibility and repeatability of finger movements during typing: Analysis of multiple degrees of freedom," *J. Comput. Neurosci.*, vol. 4, no. 1, pp. 29–46, 1997.

[8] V. C. K. Cheung, L. Piron, M. Agostini, S. Silvoni, A. Turolla, and E. Bizzi, "Stability of muscle synergies for voluntary actions after cortical stroke in humans.," *Proc. Natl. Acad. Sci. U. S. A.*, vol. 106, no. 46, pp. 19563–19568, 2009.

[9] M. C. Tresch, V. C. K. Cheung, and A. D'Avella, "Matrix factorization algorithms for the identification of muscle synergies: evaluation on simulated and experimental data sets.," *J. Neurophysiol.*, vol. 95, no. 4, pp. 2199–2212, 2006.

[10] A. d'Avella, M. Giese, Y. P. Ivanenko, T. Schack, and T. Flash, "Editorial: Modularity in motor control: from muscle synergies to cognitive action representation," *Front. Comput. Neurosci.*, vol. 9, no. October, pp. 1–6, 2015.

[11] M. C. Tresch and A. Jarc, "The case for and against muscle synergies," *Curr. Opin. Neurobiol.*, vol. 19, no. 6, pp. 601–607, 2009.

[12] M. P. Rearick, A. Casares, and M. Santello, "Task-dependent modulation of multi-digit force coordination patterns.," *J. Neurophysiol.*, vol. 89, no. 3, pp. 1317–1326, 2003.

[13] E. Todorov and Z. Ghahramani, "Analysis of the synergies underlying complex hand manipulation.," *Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, pp. 4637–4640, 2004.

[14] K. M. Steele, M. C. Tresch, and E. J. Perreault, "Consequences of biomechanically constrained tasks in the design and interpretation of synergy analyses," *J. Neurophysiol.*, vol. 113, no. 7, pp. 2102–2113, 2015.

[15] N. Lambert-Shirzad and H. F. M. Van der Loos, "On identifying kinematic and muscle synergies: a comparison of matrix factorization methods using experimental data from the healthy population," *J. Neurophysiol.*, vol. 117, no. 1, pp. 290 – 302, Jan. 2017.

[16] P. V. McDonald, S. K. Oliver, and K. M. Newell, "Perceptual-motor exploration as a function of biomechanical and task constraints," *Acta Psychol. (Amst).*, vol. 88, no. 2, pp. 127–165, Mar. 1995.

[17] F. C. Huang and J. L. Patton, "Individual patterns of motor deficits evident in movement distribu6on analysis," in *IEEE International Conference on Rehabilitation Robotics (ICORR)*, 2013, pp. 1–6.

[18] J. Lancaster, Z. Wright, F. Huang, and J. Patton, "The effects of motor impairments on movement distributions," in *International Conference of the IEEE Engineering in Medicine and Biology Society EMBC*, 2014.

[19] B. A. Valdés, N. Shirzad, C. Hung, H. F. M. Van der Loos, and S. M. N. Glegg, "Visualisation of two-dimensional kinematic data from bimanual control of a commercial gaming system used in post-stroke rehabilitation," in *In Proceedings of International Conference on Virtual Rehabilitation ICVR*, 2015.

[20] G. Kwakkel, B. Kollen, and E. Lindeman, “Understanding the pattern of functional recovery after stroke: facts and theories,” *Restor. Neurol. Neurosci.*, vol. 22, no. 3–5, pp. 281–299, 2004.

[21] N. Lambert-Shirzad and H. F. M. Van der Loos, “An Empirical Study of Factorization Methods to Quantify Motor Synergies,” in *Proceedings of the 3rd International Conference on NeuroRehabilitation, ICNR*, 2016, pp. 1145–1149.

[22] N. Shirzad, B. A. Valdés, C. Hung, M. Law, J. Hay, and H. F. M. Van der Loos, “FEATHERS, a bimanual upper limb rehabilitation platform: A case study of user-centred approach in rehabilitation device design,” in *In Proceedings of International Conference on Engineering Design ICED*, 2015.

[23] S. Muceli, A. T. Boye, A. D’Avella, and D. Farina, “Identifying representative synergy matrices for describing muscular activation patterns during multidirectional reaching in the horizontal plane.,” *J. Neurophysiol.*, vol. 103, no. 3, pp. 1532–1542, 2010.

[24] R. Gentner, T. Edmunds, D. K. Pai, and A. D’Avella, “Robustness of muscle synergies during visuomotor adaptation,” *Front. Comput. Neurosci.*, vol. 7, no. 120, pp. 1–12, 2013.

[25] J. Roh, W. Z. Rymer, and R. F. Beer, “Evidence for altered upper extremity muscle synergies in chronic stroke survivors with mild and moderate impairment,” *Front. Hum. Neurosci.*, vol. 9, no. February, pp. 1–14, 2015.

[26] K. M. Steele, M. C. Tresch, and E. J. Perreault, “The number and choice of muscles impact the results of muscle synergy analyses,” *Front. Comput. Neurosci.*, vol. 7, no. August, p. 105, 2013.

[27] H. J. Hermens, B. Freriks, R. Merletti, D. Stegeman, J. Blok, G. Rau, C. Disselhorst-Klug, and G. Hägg, “European Recommendations for Surface ElectroMyoGraphy,” *Roessingh Res. Dev.*, pp. 8–11, 1999.

[28] J. Roh, W. Z. Rymer, E. J. Perreault, S. B. Yoo, and R. F. Beer, “Alterations in upper limb muscle synergy structure in chronic stroke survivors,” *J. Neurophysiol.*, vol. 109, no. 3, pp. 768–81, 2013.

[29] S. Choppin and J. Wheat, “The potential of the Microsoft Kinect in sports analysis and biomechanics,” *Sport. Technol.*, vol. 6, no. 2, pp. 78–85, 2013.

[30] D. Webster and O. Celik, “Experimental evaluation of Microsoft Kinect’s accuracy and capture rate for stroke rehabilitation applications,” *IEEE Haptics Symp. HAPTICS*, pp. 455–460, 2014.

[31] K. R. S. Holzbaur, W. M. Murray, and S. L. Delp, “A model of the upper extremity for simulating musculoskeletal surgery and analyzing neuromuscular control,” *Ann. Biomed. Eng.*, vol. 33, no. 6, pp. 829–840, 2005.

[32] S. L. Delp, F. C. Anderson, A. S. Arnold, P. Loan, A. Habib, C. T. John, E. Guendelman, and D. G. Thelen, “OpenSim: Open-source software to create and analyze dynamic simulations of movement,” *IEEE Trans. Biomed. Eng.*, vol. 54, no. 11, pp. 1940–1950, 2007.

[33] R. M. Enoka, *Neuromechanics of Human Movement*, 5th ed. Human Kinetics, 2015.

[34] D. J. Berger and A. d’Avella, “Effective force control by muscle synergies,” *Front. Comput. Neurosci.*, vol. 8, no. April, pp. 1–13, 2014.

[35] E. Bizzi and V. C. K. Cheung, “The neural origin of muscle synergies,” *Front. Comput. Neurosci.*, vol. 7, no. April, p. 51, 2013.

[36] Z. A. Wright, M. E. Fisher, F. C. Huang, and J. L. Patton, “Data sample size needed for prediction of movement distributions,” in *International Conference of the IEEE Engineering in Medicine and Biology Society EMBC*, pp. 5780–5783, 2014.

[37] M. Lam, S. Tatla, K. Lohse, N. Shirzad, A. Hoens, K. Miller, N. Virji-Babul, H.F.M. Van der Loos, “Perceptions of technology and its use for therapeutic application for individuals with hemiparesis: findings from adult and pediatric focus groups,” *JMIR Rehabil Assist Technol*, vol. 2, no. 1, e1, 2015.

[38] S. Tatla, N. Shirzad, K. Lohse, N. Virji-Babul, A. Hoens, L. Holsti, L. Li, K. Miller, M. Lam, H.F.M. Van der Loos, “Therapists' perceptions of social media and video game technologies in upper limb rehabilitation,” *JMIR Serious Games*, vol. 3, no. 1, e2, 2015.

[39] N. Shirzad, H.F.M. Van der Loos, “Error amplification to promote motor learning and motivation in therapy robotics,” in *IEEE Engineering in Medicine and Biology Society EMBC*, pp. 3907–3910,2012.

[40] N. Shirzad, H.F.M. Van der Loos, “Adaptation of task difficulty in rehabilitation exercises based on the user's motor performance and physiological responses,” in *IEEE International Conference on Rehabilitation Robotics ICORR*, p. 1–6, 2013.

[41] N. Shirzad, H.F.M. Van der Loos, “Evaluating the user experience of exercising reaching motions with a robot that predicts desired movement difficulty,” *J. Mot. Behav.*, vol. 48, no.. 1, pp. 31–46, 2016.

[42] B. A. Valdés, C. G. E. Hilderman, C. .T. Hung, N. Shirzad, H.F.M. Van der Loos, “Usability testing of gaming and social media applications for stroke and cerebral palsy upper limb rehabilitation,” in *International Conference of the IEEE Engineering in Medicine and Biology Society EMBC*, pp. 3602–3605, 2014.