On the Relationship Between Human Motor Control Performance and Kinematic Synergies in Upper Limb Prosthetics

Ricardo Garcia-Rosas, Denny Oetomo, Chris Manzie, Ying Tan, and Peter Choong

***Abstract*— Current prosthesis command interfaces only allow for a single degree of freedom to be commanded at a time, making coordinated motion difficult to achieve. Thus it becomes crucial to develop methods that complement these interfaces to allow for intuitive coordinated arm motion. Kinematic synergies have been shown as an alternate method where the motion of the prosthetic device is coordinated with that of the residual limb. In this paper, the mapping between the parameters of a kinematic synergy model and a measure of task performance is established experimentally in order to test the applicability of online optimization methods for the identification of synergies. To achieve this, a cost function that captures the objective of the reaching task and a linear kinematic synergy model were chosen. A human experiment was developed in a Virtual Reality (VR) platform in order to determine the synergy-performance relationship. The experiments were performed on 10 able-bodied subjects. The relationship observed between the synergy parameter and the reaching task cost function suggests existing online optimization methods may be applicable.**

I. INTRODUCTION

The command interfaces available to current robotic prosthetic arms usually include a combination of proportional surface electromyography (sEMG) sensors and buttons or smartphone applications. However, these interfaces only allow for continuous control of a single degree of freedom (DOF). Given this difference between prosthesis DOF and interface signals, complex coordinated motion of the whole human-prosthesis arm is unavailable to their users. These difficulties and complexity have been linked to device abandonment [1]. Thus it is important to develop methods that can complement sEMG and allow for intuitive coordinated arm motion in prosthetics.

One of such methods is based on the theory of muscle synergies, which states that muscles are grouped by the Central Nervous System (CNS) in order to regulate complex coordinated motion in a simplified manner [2]. Similarly, synergies can represent the relationships between the DOF of a limb; these are known as kinematic synergies [3]. Kinematic synergies have been proposed as an alternate method to sEMG for providing commands to a prosthetic arm [4], allowing prosthesis users to perform coordinated arm motion. Given that fine motion of the residual limb is typically still available to amputees, synergistic prosthesis interfaces may provide an advantage over purely sEMG interfaces where fine regulation of the signals is difficult.

This project is partially funded by the Valma Angliss Trust and Defence Science Technology Group CERA program.

R. Garcia-Rosas, D. Oetomo, C. Manzie and Y. Tan are with the School of Electrical, Mechanical and Infrastructure Engineering, and P. Choong with the Department of Surgery, The University of Melbourne, VIC 3010, Australia. ricardog@student.unimelb.edu.au; {doetomo,manziec,yingt,pchoong}@unimelb.edu.au.

Current synergistic approaches to prosthesis arm motion regulation utilize Artificial Neural Networks (ANNs), where an ANN is used to coordinate motion of the residual and prosthetic limb [4], [5]. In order to determine their relationship, the ANN is trained using machine learning methods with reaching motion data-sets gathered from able-bodied subjects [5]. While these methods have shown promising results, the ANNs have been observed to be sensitive to individual variation. This may produce a challenge for generalizing the approach to subjects outside the training set [5]. Retraining of the ANN for an amputee may not be possible as training data requires full reaching motion [4], [5]. While these methods identify averaged synergies for the training group, it has been shown that optimal synergies can vary across individuals [6]. Furthermore, natural motion in amputees can vary significantly from that of able-bodied people due to the changes in the limb dynamics and constraints as a result of the amputation.

A method for identifying the optimal synergies for a given individual has the potential to allow the algorithms to adapt to their users and their changes in behavior. This need has been explicitly identified in pre-clinical studies with synergistic prostheses [7], motivating the consideration of online optimization methods, such as Extremum Seeking (ES) [8], in order to identify such synergies. A feasibility study with such technique was performed by the authors [9], where appropriate assumptions on human motor control dynamics were needed, such as the existence of a local extremum in the input/output map of interest [10, Assumption 2]; which is a common requirement for gradient based online optimization methods. It is established in the literature that human motor control strategy converges to a particular trajectory of task execution when the task is learned (e.g. [11]). What the present study seeks to establish is that given a range of possible kinematic synergies, when all the synergies are learned by the human (rather than focusing on a single synergy), there exists one where the performance of the task is better, by a specified measure, than with other synergies.

In this paper, the relationship between the parameters of a synergy model and a measure of task performance (or cost) is established experimentally in order to test the applicability of online optimization methods for the identification of synergies. To achieve this, a cost function that captures the objective of the reaching task and a linear kinematic synergy model were chosen without loss of generalization to other approaches that are linear in their parametrization. A human experiment to determine the synergy-performance relationship for a set of synergies was developed in a Virtual Reality (VR) platform. The experiment was performed on 10 able-bodied subjects. The Institution's Ethical Review Board approved all experimental procedures involving humans.

II. Methodology

A. Model of kinematic synergy

There exist multiple approaches to represent muscle and kinematic synergies, both non-model [5] and model based [12]. Given that the focus of this work is on finding the relationship between synergies and task performance rather than the choice of synergies, a shoulder-elbow linear synergy model was chosen. Linear synergies have been observed to occur between the shoulder and elbow during reaching motion [13]. Furthermore, they have been used to model upper limb muscle synergies and their linear combination can produce complex motion as observed in [12]. In the case of kinematic synergies, the velocities of the DOF of the limb are the ones being coordinated [5].

Let the residual limb joint velocities $\dot{\mathbf{q}}_r$, in this case the shoulder, be given by $\dot{\mathbf{q}}_r = \begin{bmatrix} \dot{q}_{fle} & \dot{q}_{abd} & \dot{q}_{rot} \end{bmatrix}^T$, where $\dot{q}_{fle}$, $\dot{q}_{abd}$, $\dot{q}_{rot}$ are scalar and represent shoulder flexion/extension, abduction/adduction, and humeral rotation respectively. Similarly, let prosthesis joint velocities $\dot{\mathbf{q}}_p$, in this case the elbow, be given by $\dot{\mathbf{q}}_p = \dot{q}_{elb}$, where the scalar $\dot{q}_{elb}$ represents elbow flexion/extension. Then, a linear kinematic synergy is given by $\dot{\mathbf{q}}_p = \boldsymbol{\theta}\dot{\mathbf{q}}_r$, where $\boldsymbol{\theta}$ represents the synergy parameters and is restricted to a compact set Θ which includes the physically feasible parameters. Then the desired elbow velocity provided by the synergy can be used to generate a reference for the prosthesis controller as is shown in Figure 1, where the controller is a predetermined feedback controller. Experimentally identifying the optimal parameters $\boldsymbol{\theta}^*$ for a group of individuals and the relationship of $\boldsymbol{\theta}$ to task performance will be the main objective of this work.

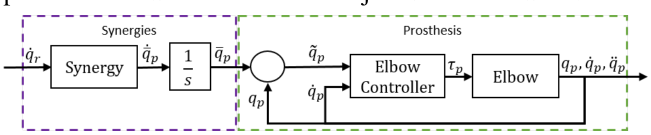


Fig. 1. Synergistic prosthetic elbow block diagram.

B. Reaching task characterization

A widely accepted method for modelling trajectory planning and generation in the CNS is to characterize motor control performance with a cost function which is optimized to determine the desired hand trajectory. Multiple cost function based motion characteristics have been proposed in the literature such as tracking error, torque-change, and hand jerk [14]. Given the application and experimental hardware setting, tracking and hand jerk are more feasible for measurement than other methods.

Therefore, the cost function that characterizes motor control performance of a reaching task can be described by

$$J(\boldsymbol{\theta}) = \sum_{j=1}^{M} \alpha_j \psi_j(\boldsymbol{\theta}), \quad (1)$$

where $M > 0$ is the number of motion characteristics in the cost function, $\alpha_j > 0$ the weight given to each characteristic, and the positive function $\psi_j(\cdot)$ represents a motion characteristic. In this work two motion characteristics were considered: $\psi_1(\cdot)$ the tracking error, and $\psi_2(\cdot)$ hand jerk, which are given by

$$\psi_1 = \|\mathbf{p}^i(T_f^i, \boldsymbol{\theta}) - \bar{\mathbf{p}}_f\|^2, \quad \psi_2 = \int_{T_o}^{T_f^i} \|\dddot{\mathbf{p}}^i(t, \boldsymbol{\theta})\|^2 dt, \quad (2)$$

where i represents an iteration of the task, T_o is the start time of the motion, which is constant across all iterations, and $T_f^i > 0$ is the motion end time which can vary across iterations. Moreover, it has $t_o \leq T_o \leq T_f^i \leq t_{f,max}$.

C. Experiment description and protocol

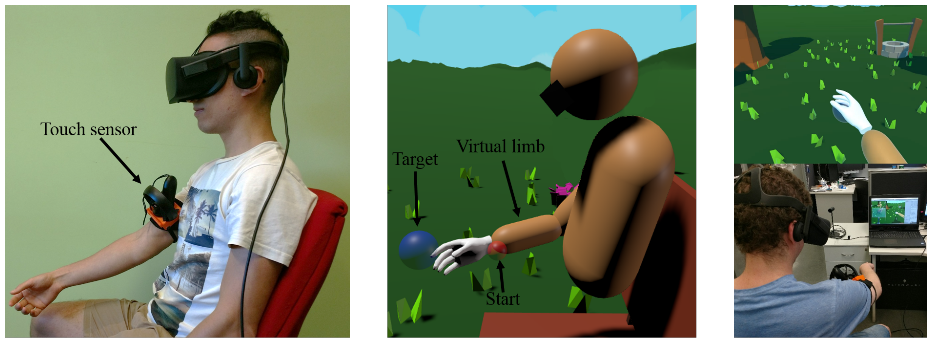
Subjects performed a center-out forward reaching task from a seated position while using a virtual synergistic prosthetic elbow. The start and end positions were constant throughout the experiment and were shown in the VR environment as presented in Figure 2.B. The scalar parameter θ chosen for the experiment was the one related to shoulder flexion/extension $\dot{q}_{fle}$, and 10 different values were explored. In order to be able to observe the mapping between Synergy and Performance, it was necessary to isolate the transient behavior due to task learning. Thus subjects repeated the reaching task for each value until it was deemed as learned.

Learning of the task was determined by the variability of the trajectory followed by the hand, with the successfully learned task condition being reaching a variability radius under $\Delta_p = 2$cm. This condition was determined by following studies that demonstrated that as humans learn a hand reaching task, the variability of hand trajectories is reduced [15]. The $\Delta_p = 2$cm radius was chosen by testing the reaching capabilities of able-bodied people, hardware tracking precision, and additional tolerance to account for the virtual prosthesis.

Trajectory variability was determined by sampling hand trajectory and evaluating it at fixed time steps. Trajectory mean and standard deviation was calculated for a sliding window of 10 task repetitions at each sampling time step. This was used to generate a spheroid centered at the mean hand position with radius given by the standard deviation. The set of spheroids represents the mean trajectory and standard deviation [16]. The learning condition is achieved when the radius of all spheroids is smaller or equal to Δ_p.

The experiment was performed on 10 able-bodied subjects (A-J). The forward reaching task was repeated a minimum of 10 times and maximum of 50 times for each parameter to be analyzed, with successful learning triggering a parameter change. The parameter values for each subject were manually determined by the experimenter in order to explore the regions of the parameter space best suited to each subject, with the first three values being predetermined to 1.5, 1.1, and 1.9, in the respective order. Subsequent values were chosen by alternating between the extremes of the identified search region in order to minimize skill transfer between synergy values. Cost functions (ψ_1, ψ_2) were normalized to be within the same range (0-1) and equal weights were given to them ($\alpha_1 = \alpha_2 = 1$). Each reaching motion had a time limit of 3 seconds. Sessions were separated in five blocks:

1) Hardware calibration (5 minutes).
2) VR training (2 minutes).



A) B) C)

Fig. 2. Experiment platform set-up: A) Subject position and sensor placing. B) Subject in virtual environment. C) Subject and VR views.

3) Experiment task block 1 (25 minutes).
4) VR rest (5 minutes).
5) Experiment task block 2 (25 minutes).

During hardware calibration, the sensor and virtual upper arm were calibrated such that the virtual upper arm matched the dimensions and motion of the subject's upper arm. Subjects were allowed to rest for 1 minute every 50 repetitions in order to minimize upper arm fatigue. A longer rest was given in between experiment blocks, where subjects removed the VR headset in order to minimize VR fatigue. The procedure was approved by the Institution's Ethical Review Board under project number 1750711.1.

D. Hardware set-up and data gathering

The VR experiment platform was developed on an Oculus Rift headset with the application developed in Unity3D. The experiment was run on an Intel Core i7-7700HQ processor at 3.8GHz, with 16GB RAM, and an NVIDIA GeForce GTX 1070 video card with 8GB GDDR5. The Oculus Rift set-up included 3 tracking sensors, two placed in the front corners of the room and one in a back corner, and one Oculus Touch controller. Virtual residual limb motion was determined by a Touch controller attached to the subject's dominant upper arm as shown in Figure 2.A. Motion of the lower arm had no effect on the motion of the virtual arm. Data gathering and VR update was performed at 90Hz. The subject's shoulder rotation and angular velocity in 3 DOF, the rotation and angular velocity of the virtual prosthetic elbow, and hand position and velocity in 3D space were gathered.

III. Results and Discussion

Subjects were able to maintain a consistent level of trajectory variability across iterations, converging asymptotically to the desired threshold (Δ_p) as learning occurred, as has been observed with performance in other works [11]. Representative results of this are shown in Figure 3.A, where variability across iterations for subject E is presented. The sudden increases in variability are due to a change of θ value, which has been previously observed in humans when subjected to changing system dynamics [17]. In a few subjects where slower learning rate was observed, convergence to the desired level of trajectory variability Δ_p was not achieved within the allotted number of iterations in the experiment. In these cases, variability was observed to increase towards the last iterations as can be seen in Figure 3.B. This may be attributed to fatigue due to the larger number of repetitions performed during the experiment. These results suggests that the chosen learning condition should be able to accommodate for individual capabilities, learning rates and performance variation throughout the use of the device to properly isolate the transient behavior caused by human learning dynamics.

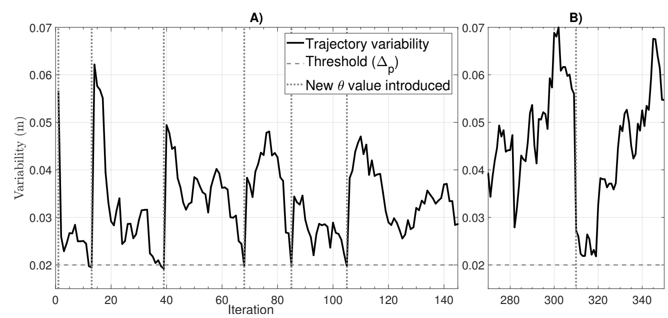


Fig. 3. A) Subject E (whole experiment) and B) Subject F (last two θ values) trajectory variability across task iterations.

Figure 4 presents the relationship between the proposed cost function (J) in Equation (1) and the synergy parameter values (θ) for all able-bodied subjects (A-J), where the last 10 iterations per value (as per the learning condition presented in Section II-C) were used to generate the box and whiskers plots. It was observed that the performance range (J) differs across individuals, and that the minimum cost (J^*) was observed at different synergy parameter values (θ^*) for different subjects. This highlights both individual variability in performance (J) and in synergies (θ). Furthermore, when the average best synergy across all subjects ($\theta^*_\mu = 1.7$) is considered and performance evaluated, it can be observed that for some subjects performance would be significantly impaired, e.g. by 32% for subject D and 66% for subject I. This highlights the significance of finding the best synergy for each individual.

The purpose of this work aimed to observe a unique minimum in the Performance/Synergy $J(\theta)$ map for each person. Due to the relatively low number of subjects, a statistically significant quadratic map was not obtained. However, it can be observed in the subjects that achieved lower variability, see Figure 4.A-B and D-E, that there is a trend towards exhibiting a unique minimum as the task is learned; since lower variability can be attributed to learning of a task [15]. This difference in learning of the task across subjects may be attributed to the different learning rates across individuals [11]. Such that the individuals that were able to learn the task

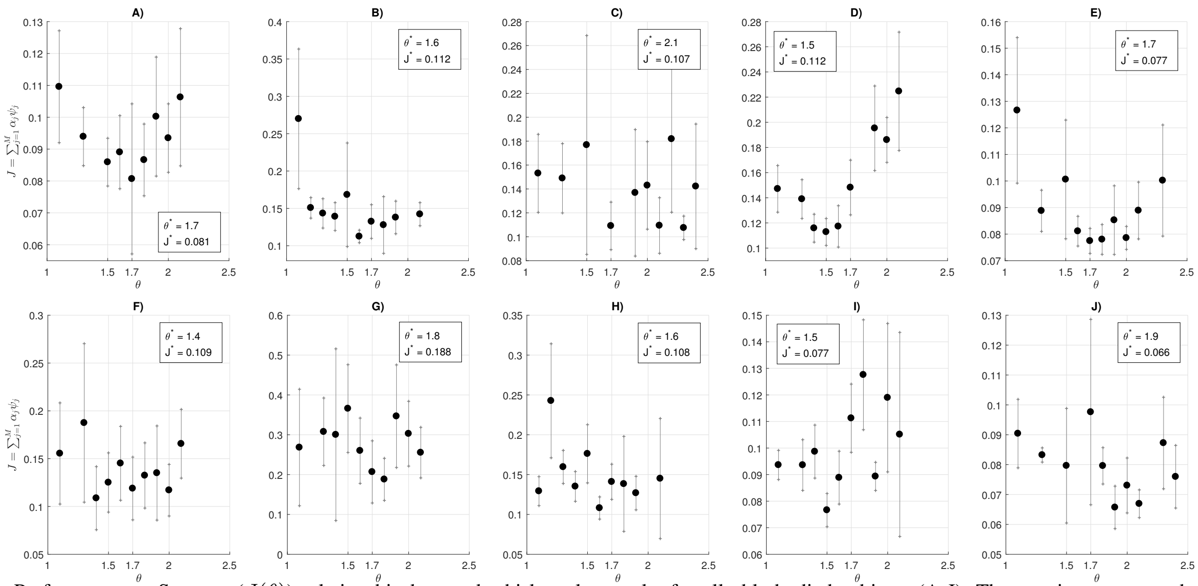


Fig. 4. Performance vs Synergy ($J(\theta)$) relationship box and whisker plot results for all able-bodied subjects (A-J). The x-axis represents the synergy parameter values and the y-axis the cost. Circles represent the mean cost and lines the standard deviation.

within the allocated iterations show a result more reflective of a quadratic map (e.g. A-B, D-E). This may suggest that when the task is yet to be "learned", the $J(\theta)$ map is unreliable for the proposed purposes. On the other hand, as the task is learned and trajectories become more consistent, the map shows properties desirable for online optimization algorithms, such as a local unique extremum.

IV. Conclusion

An experiment to determine the relationship between the parameters of a linear synergy (θ) and a measure of motor control performance (J) that characterizes a reaching task was presented. This experiment extended from typical experiments on human motor control by the exploration and learning of different motion settings, in the form of synergy parameters, rather than the learning of a single one. It was observed that values of the cost function differ across individuals, and that the minimum cost was observed for different synergy parameter values for different subjects. This highlights individual variability in performance, but also in synergies. While a statistically significant quadratic map was not obtained, it was observed that there is a trend towards exhibiting a unique minimum as the task is learned. This observation suggests that as the task is learned, the map obtained from the experiment shows properties desirable for online optimization algorithms. This highlights the importance of developing a design framework that can determine successful learning of the task while accounting for individual capabilities, learning rate and filtering external disturbances. Future work will investigate the implementation of the identification algorithm in the VR experimental platform, to develop a method for triggering algorithm that can update based on the learning condition, and to conduct an experiment to demonstrate the performance of the algorithm.

References

[1] E. Biddiss and T. Chau, "Upper-limb prosthetics: critical factors in device abandonment.," *Am. J. Phys. Med. Rehabil.*, vol. 86, no. 12, pp. 977–987, 2007.

[2] J. F. Soechting and F. Lacquaniti, "Invariant characteristics of a pointing movement in man," *J. Neurosci.*, vol. 1, no. 7, 1981.

[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, 2015.

[4] R. R. Kaliki, R. Davoodi, and G. E. Loeb, "Evaluation of a noninvasive command scheme for upper-limb prostheses in a virtual reality reach and grasp task," *IEEE Trans. Biomed. Eng.*, vol. 60, no. 3, 2013.

[5] M. Merad, A. Roby-Brami, and N. Jarrasse, "Towards the implementation of natural prosthetic elbow motion using upper limb joint coordination," in *IEEE RAS EMBS Int. Conf. Biomed. Robot. Biomechatronics*, pp. 821–826, 2016.

[6] L. Tang, F. Li, S. Cao, X. Zhang, and X. Chen, "Muscle synergy analysis for similar upper limb motion tasks," in *Conf. IEEE Eng. Med. Biol. Soc.*, pp. 3590–3593, 2014.

[7] M. Merad, E. de Montalivet, A. Touillet, N. Martinet, A. Roby-Brami, and N. Jarrassé, "Pre-clinical evaluation of a natural prosthetic elbow control strategy using residual limb motion and a model of healthy inter-joint coordinations," *Ann. Phys. Rehabil. Med.*, vol. 60, 2017.

[8] Y. Tan, W. Moase, C. Manzie, D. Nesic, and I. Mareels, "Extremum seeking from 1922 to 2010," *Chinese Control Conf.*, pp. 14–26, 2010.

[9] R. Garcia-Rosas, Y. Tan, D. Oetomo, and C. Manzie, "On-line synergy identification for personalized active arm prosthesis: a feasibility study," in *Am. Control Conf.*, 2018.

[10] D. Nesic, A. Mohammadi, and C. Manzie, "A framework for extremum seeking control of systems with parameter uncertainties," *IEEE Trans. Automat. Contr.*, vol. 58, no. 2, pp. 435–448, 2013.

[11] S.-H. Zhou, D. Oetomo, Y. Tan, E. Burdet, and I. Mareels, "Modeling individual human motor behavior through model reference iterative learning control.," *IEEE Trans. Biomed. Eng.*, vol. 59, no. 7, 2012.

[12] M. Chhabra and R. A. Jacobs, "Properties of synergies arising from a theory of optimal motor behavior.," *Neural Comput.*, vol. 18, no. 10, pp. 2320–2342, 2006.

[13] G. L. Gottlieb, Q. Song, D. A. Hong, G. L. Almeida, and D. Corcos, "Coordinating movement at two joints: a principle of linear covariance.," *J. Neurophysiol.*, vol. 75, no. 4, pp. 1760–4, 1996.

[14] D. A. Kistemaker, J. D. Wong, and P. L. Gribble, "The cost of moving optimally: kinematic path selection," *J. Neurophysiol.*, vol. 112, no. 8, pp. 1815–1824, 2014.

[15] W. G. Darling and J. D. Cooke, "Changes in the variability of movement trajectories with practice," *J. Mot. Behav.*, vol. 19, no. 3, pp. 291–309, 1987.

[16] A. P. Georgopoulos, J. F. Kalaska, and J. T. Massey, "Spatial trajectories and reaction times of aimed movements: effects of practice, uncertainty, and change in target location.," *J. Neurophysiol.*, vol. 46, no. 4, pp. 725–743, 1981.

[17] F. Matveeva, S. A. S. Mousavi, X. Zhang, T. M. Seigler, and J. B. Hoagg, "On the effects of changing reference command as humans learn to control dynamic systems," in *Conf. Decis. Control*, 2016.