Natural Myocontrol in a Realistic Setting: a Comparison Between Static and Dynamic Data Acquisition

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***Abstract*— Natural myocontrol employs pattern recognition to allow users to control a robotic limb intuitively using their own voluntary muscular activations. The reliability of myocontrol strongly depends on the signals initially collected from the users, which must appropriately capture the variability encountered later on during operation. Since myoelectric signals can vary based on the position and orientation of the limb, it has become best practice to gather data in multiple body postures. We hereby concentrate on this acquisition protocol and investigate the relative merits of collecting data either statically or dynamically. In the static case, data for a desired hand configuration is collected while the users keep their hand still in certain positions, whereas in the dynamic case, data is collected while users move their limbs, passing through the required positions with a roughly constant velocity.**

Fourteen able-bodied subjects were asked to naturally control two dexterous hand prostheses mounted on splints, performing a set of complex, realistic bimanual activities of daily living. We could not find any significant difference between the protocols in terms of the total execution times, although the dynamic data acquisition was faster and less tiring. This would indicate that dynamic data acquisition should be preferred over the static one.

I. Introduction

Pattern recognition (PR) has the potential to allow dexterous robotic hands to be controlled via natural muscle activations. The idea is that algorithms fed with sufficient training data can transparently recognize which hand posture the human user intends to perform just by analyzing their myoelectric signals [1]. The main driver for research on this topic has been the desire to restore the dexterity of upper-limb amputated patients via articulated prosthetic limbs [2]. In recent years, other applications for natural myocontrol have been proposed, such as robotic teleoperation [3] or rehabilitation of stroke patients [4].

Surface electromyography (sEMG) has been the principal control modality for powered hand prostheses [5], due to its non-invasiveness and relatively low cost. A complicating factor of sEMG in the context of natural myocontrol is the *limb position effect* [6, 7, 8, 9, 10, 11], namely the change in signals depending on the position and orientation of the limb (body posture). The application of PR by its very nature requires training data that sufficiently captures these variations and it has therefore become best-practice to perform the acquisition procedure in multiple positions [6, 8, 12]. Although this strategy seems to be effective in addressing the limb position effect, it comes at the cost of a considerably longer and more tiring acquisition protocol. The duration and comfort of such protocols have a significant impact on the usability of myoelectric systems because they need to be re-calibrated regularly with new data during daily use [13]. There have been efforts to limit this increase in collection time by replacing a static posture in multiple positions with a single dynamic movement that passes through these positions. Scheme et al. [7] showed that such a dynamic protocol not only sped up the acquisition, but also improved recognition rates in static positions as well as during arm movements that simulate simple tasks (e.g., moving an object). Similar results were reported by Yang et al. [14], who additionally showed a benefit in including multiple levels of muscle contractions. These studies provide support for collecting data for natural myocontrol in a swift dynamic manner. Nonetheless, in both cases the performance was measured in terms of offline classification accuracy. This metric has been shown to be only weakly related to online control performance [15, 16]. It is therefore not clear if the claimed benefits actually materialize when the models are tested online and with the human in a closed control loop.

In this study, we aim to address this shortcoming. To do so, we tested both static and dynamic data acquisition with an online evaluation and in a realistic daily-living setting. We asked fourteen able-bodied subjects to follow both protocols and then we fitted them with two commercially available, dexterous prostheses mounted on splints. With this equipment, they were required to perform a set of bimanual activities of daily living (ADLs) in a simulated domestic environment. We intentionally selected bilateral prostheses and activities to avoid the pitfall of users over-relying on their unaffected limb to execute the activities [17]. Furthermore, this also ensures that our study applies equally to a teleoperation scenario. We measured performance quantitatively by means of the completion times of the ADLs.

In the following, we thoroughly describe the experimental setup and protocol in section II. The results of our experiment and a discussion thereof are presented in section III, while the conclusions are drawn in section IV.

II. Materials and Methods

We hereby compare the effectiveness of a static and a dynamic protocol for acquiring the forearm sEMG of grasps performed in multiple arm positions. After either acquisition, the recorded myoelectric signals were used to train a bilateral upper limb prosthetic system. Subsequently, the system was tested by carrying out a series of bimanual ADLs.

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A. Participants

Fourteen able-bodied subjects participated in the experiment (age 27.9 ± 5.8 years, 10 men and 4 women). Before the experiment, they received an oral and written description and signed an informed consent form. The study was conducted at the German Aerospace Center according to the WMA Declaration of Helsinki and approved by the Institution's internal committee for personal data protection.

B. Experimental setup

1) Bilateral setup and domestic environment: We designed a bilateral manipulation setup that allowed able-bodied subjects to simultaneously and proportionally control two prosthetic hands. Two Myo bracelets by Thalmic Labs [18] were placed about 5 cm below the subjects' elbows. Each of them provided 8-channel sEMG of the forearm muscles at a sampling rate of around 200 Hz. A couple of orthotic splints were used to fix two *i-LIMB*^{TM} *Revolution* prosthetic hands by Touch Bionics [19] at the extremity of each arm of the user. These prosthetic hands comprise six motors under direct independent current (i.e., torque) control, which actuate flexion/extension of the five fingers plus abduction/adduction (rotation) of the thumb. All devices communicated serially over Bluetooth with a laptop that guided users during the data acquisition, processed the data, trained and ran the controller of each prosthesis.

The experiment was conducted in a domestic-like environment consisting of a table, three shelves at different heights (low, medium, high), a clothesline and several household items. The study was videotaped for offline performance assessment. An overview of the setup and environment is shown in Figure 1a.

2) Data processing and regression: Our custom acquisition software labeled and processed input data at runtime. The signal from each sEMG channel was rectified and low-pass filtered with a second order Butterworth filter with cut-off frequency of 1 Hz. Two instances of Ridge Regression (RR), one per arm, were trained with the data of the respective limb. Their capacity was increased by applying a Random Fourier Features (RFFs) mapping [20], which approximates a Gaussian kernel in finite dimensionality. The resulting non-linear method is computationally efficient and has been used previously in the context of myocontrol [21, 22]. The regularization parameter λ of each regressor was set to 1, while the bandwidth γ and the dimensionality D of the RFF mapping to 2 and 300, respectively. Since the real-valued outputs of the regressors were interpreted directly as torque commands for the motors of the prosthetic hands, this setup allowed simultaneous and proportional control of all six degrees of freedom (DOFs).

C. Experimental protocol

All subjects in the study tested both the static and dynamic data acquisition protocols. After each data collection, the system was trained and the participants were asked to perform a sequence of bimanual activities. This sequence was repeated twice: the first time to let the users familiarize theirselves with the prosthetic control, the second time to measure their performance. These four segments of the experiment are reported in Table I. To counterbalance any learning effects, we inverted the order for half of the subjects, that is, seven subjects started with the static acquisition protocol while the remaining seven subjects started with the dynamic one.

TABLE I: Overview of the phases in the experiment.

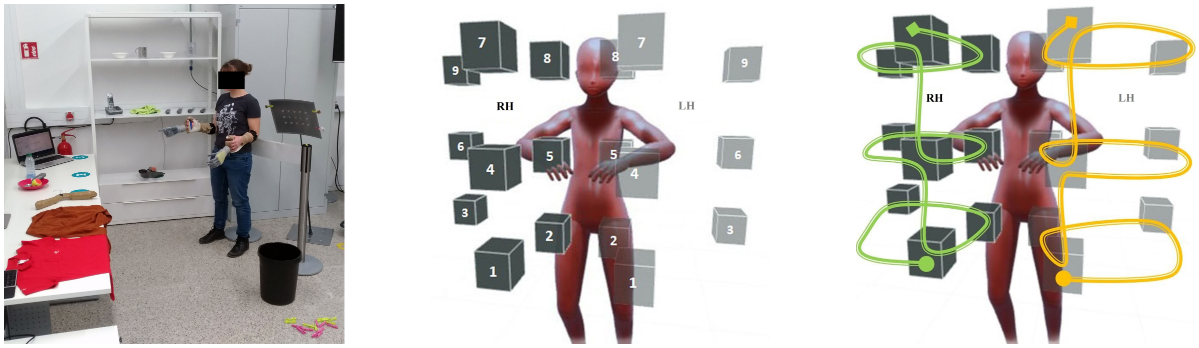
Phase#	Description
1	Collect training data using the first acquisition type
2	Familiarize on bimanual ADLs
	Evaluate performance on bimanual ADLs
3	Collect training data using the other acquisition type
4	Familiarize on bimanual ADLs
	Evaluate performance on bimanual ADLs

1) Grasps and arm configurations: During the acquisition procedure, the subjects were asked to perform some predefined combinations of grasps and arm postures while wearing the prosthetic hands. The experimenter guided the subjects through the procedure, supported by acoustic signals from the acquisition software. As grasps we selected hand rest, power grasp and index pointing. These were chosen on the base of their relevance in ADLs according to literature [23] and were sufficient to complete various demanding manipulation tasks during preliminary tests. While the users executed these grasps, we gathered the related sEMG samples and represented the grasp type in terms of the binary activation of each of the prosthesis' DOFs [22].

After reviewing the literature on the limb position effect [6, 9, 10, 11], we chose a set of nine arm positions that evenly covered the subject's reachable space. Since wrist pronation and supination have also been shown to affect myoelectric signals [14], all these positions were covered twice: first with the palm facing down and then with the palm facing up. We intentionally avoided positions in the intersection of the reachable spaces of the left and right hands, as it is uncommon for both hands to be crossed in bimanual actitivies. This constraint allowed us to speed up the procedure by acquiring every grasp simultaneously with both hands, with the arms always symmetric with respect to the sagittal plane.

2) Static protocol: Figure 1b shows the nine positions, organized in three levels (waist, chest, head) and three relative distances from the trunk (close in front, far in front, far lateral). In the static acquisition, each grasp was held in each of the 18 configurations for 3 s. We chose this duration as it was the lowest found in similar studies [6, 10, 11]. Therefore, the acquisition of each grasp took 54 s, plus a total of 72 s to switch between subsequent arm configurations. In case of fatigue, users were allowed to pause the routine and rest at any time.

3) Dynamic protocol: In the dynamic protocol, every grasp was maintained while moving the hand in a trajectory that interpolated the nine static positions, as shown in



(a) Experimental setup **(b)** Static collection **(c)** Dynamic collection

Fig. 1: *(a) Domestic-like experimental setup.* The user wore a pair of sEMG bracelets and orthotic splints to which two prosthetic hands were attached. Tableware, clothes, a telephone and other household items were placed on a table and on three shelves at different heights. *(b,c) Hand positions during static and dynamic data collection.* Solid and transparent cubes represent the selected positions of the right and left prosthetic hand, respectively. During static data acquisition, every grasp was maintained for 3 s in each position, first with the palms facing down and then up, for a total of 18 repetitions of the grasp. In the dynamic alternative, the grasps were maintained for 27 s while the hands followed a trajectory that interpolated the same nine positions. The trajectory was covered palms down from the point indicated with a circle to the square and palms up from the square to the circle.

Figure 1c. The movement started from the waist level with the palm down and proceeded upwards, passing through all nine positions. Then the user flipped the hand palm up and continued the movement backward until he returned to the starting position. The movement lasted 27 s per grasp type (i.e., half of the static acquisition), plus 4 s to prepare the following grasp. Also in this case, the users could suspend the procedure to rest.

D. *Performance evaluation*

After processing the data and training the prosthesis controllers, we evaluated the system by having the subjects perform five bimanual ADLs. These activities were inspired by those found in assessment protocols for prosthetic users (ACMC [24], SHAP [25]) and for patients with stroke-related limb impairments (CAHAI [26]). We preferred tasks that involved coordinated movements of the arms or walking and bending, as these were more susceptible to the limb position effect. The tasks are detailed in Table II. The experimenter explained the tasks to the participants before the familiarization phase. No constraint was imposed on which hand should be used to perform a particular action. The tasks proceeded without time limits and it was subjects' responsibility to recover from errors (e.g., the drop of an object).

The effectiveness of the two acquisition types was measured by timing the tasks during the evaluation phase. Based on previous work [7], we expected to find a faster total execution time when using the dynamic data acquisition. Given the limited number of participants and the within-subject study design, a one-tailed Wilcoxon signed rank test was used to identify statistically significant differences between the average task completion times. Its significance threshold was set to $\alpha = 0.05$.

TABLE II: Description of the evaluation tasks.

Task	Name	Description
T1.1	Napkin	A napkin is on the middle shelf. Take it, place it on the table and fold it twice.
T1.2	Table	A plate, glass, fork and knife are on the middle and top shelves. Take them and set a dining table.
T2.1	Water	A bottle is on the table. Unscrew the cap, pour the content of the bottle in the glass and put the bottle back in place.
T2.2	Food	A bowl is on the table. It contains a spoon and two plastic meatballs of 3 and 5 cm diameter. Use the spoon to move the meatballs into the plate.
T3	Phone	A cordless telephone is on the middle shelf. Take it, dial 9-1-1 and put it back in place.
T4	Sweep	A hand broom and a dustpan are on the lowest shelf, some clothespins and a trash bin are on the floor. Sweep the clothespins off the floor, empty the dustpan into the trash bin, put the broom and the dustpan back in place.
T5.1	Shirt	A dress shirt and a hanger are on the table. Put the shirt on the hanger, then hang the hanger on the clothes line.
T5.2	T-shirt	A T-shirt is on the table and some clothespins are pinned on a vertical support in front of the clothes line. Hang the T-shirt on the clothes line and pin it with 2 clothespins.

III. Experimental Results and Discussion

Figure 2 reports the duration of the performance evaluation session that followed the static and the dynamic data acquisition. Although the median duration of the entire task sequence is slightly lower in the dynamic case (303 s versus 319 s), we do not find any statistically significant improvement ($p > 0.05$). Moreover, the two conditions also show comparable completion times for the individual tasks (no statistically significant difference), regardless of its requirements in terms of dexterity, coordination and

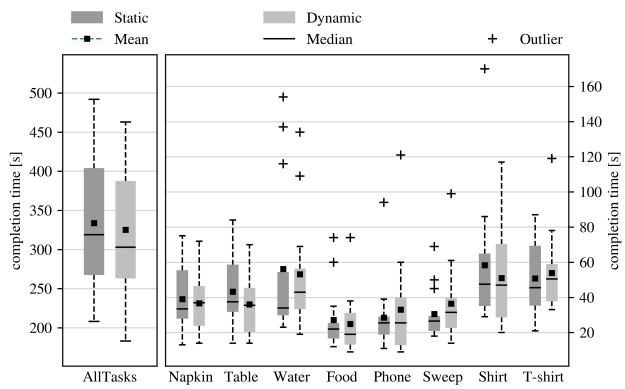


Fig. 2: *Time to complete the tasks during the performance test phase.* Median duration of the tasks and the overall task sequence during the evaluation phase of the static and dynamic data gathering. All tasks had a comparable median duration in both conditions and no significant difference was found between the average session times.

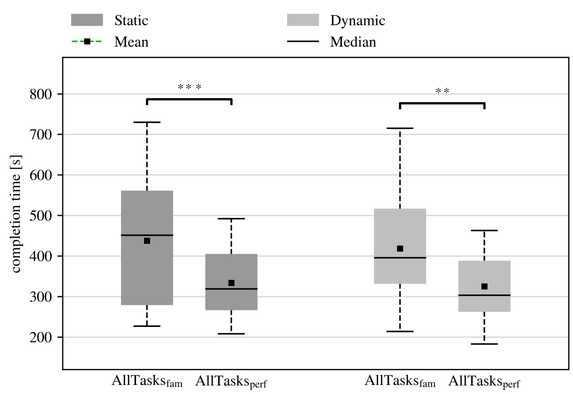


Fig. 3: *User adaptation.* Total completion time averaged over all subjects during the familiarization and the performance evaluation sessions. Despite a significant learning effect between the familiarization and performance evaluation phases of both acquisition routines (** $p < 0.01$, *** $p < 0.001$), the outcome was instead equivalent when comparing the same level of familiarization.

movements of the limbs.

The similarity in performance holds when compensating for adaptation of the subject to the experimental setup and ADLs. Figure 3 shows the duration of the familiarization and performance evaluation sessions that followed each data acquisition. On average, the subjects completed the evaluation session significantly quicker than the familiarization phase, both in the static (438 s versus 334 s, $p < 0.001$) and dynamic variant (418 s versus 325 s, $p < 0.01$). This indicates that the subjects demonstrated a strong learning effect. However, given the same level of familiarization with the system, both procedures show comparable completion times (no statistically significant difference). This implies that the equivalence between the two acquisition procedures does not depend on user adaptation.

Lastly, we measured the amount of time subjects spent

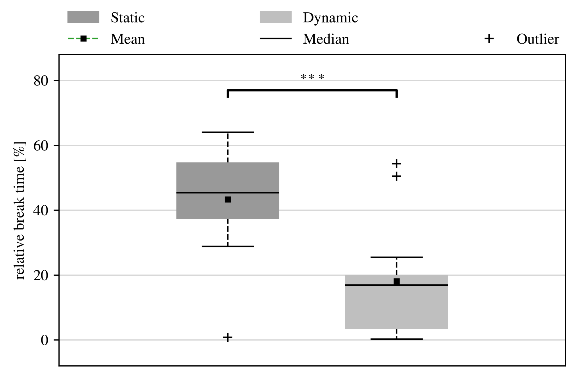


Fig. 4: *Percentage of the data collection duration spent resting.* The subjects requested significantly less break time during the dynamic data acquisition (*** $p < 0.001$).

resting and normalized it by the total acquisition time. Figure 4 shows that subjects rested significantly less during the dynamic acquisition than during the static one (a proportion of 43.3% versus 18.1%, $p < 0.001$). The dynamic acquisition protocol was therefore not only faster by design, but also easier for subjects to complete without breaks.

Discussion

We have engaged fourteen able-bodied users in a set of bilateral manipulation tasks, after they performed both a static and a dynamic data acquisition to build appropriate myocontrol models. Albeit previous studies [7, 14] showed that dynamic acquisition produces more accurate models, we did not observe any significant difference in performance between the acquisition protocols. To the best of our knowledge, this is the first time in which the comparison between such protocols is carried out online and in a completely realistic setting. Among other reasons, we argue that the similar performance of the two data collection protocols has to do with the users' ability to adapt to the situation, to the required tasks and to the unreliability of the control system. In our case this is demonstrated by the strong learning effect shown by all users when performing the tasks for the second time, even though the trained model has remained the same. Interestingly, this result might be seen as a further confirmation that offline testing of myocontrol hardly generalizes to real life [15, 16].

Given the realism of the tasks they were requested to perform, it is notable that all users were able to complete all tasks and subtasks in a reasonable amount of time. This shows that both of the data acquisition procedures provided sufficiently rich training data and that the combination of RR with RFFs is a solid basis for myocontrol. Since the acquisition procedure only required about 3 min (static) or 1.5 min (dynamic) in total, it could feasibly be performed as a calibration routine just after donning a prosthesis. This hints at the main advantage we found for the dynamic routine: while it did not increase performance, it was faster and less tiring for the users.

The results of this study are in relation to able-bodied subjects, but a few reasonable assumptions can be made as to how they can be applied to myoelectric prostheses users. Similar to intact subjects, we expect them to be able to perform manipulation tasks equivalently well regardless of the data acquisition protocol used. In fact, the ability to adapt to myocontrol that was observed in able-bodied subjects may be even greater in prosthetic users because of their previous experience with myocontrolled systems. Although dynamic data acquisition proved to be significantly more comfortable for the intact subjects in this study, the perception of comfort may change after the amputation and may depend on how the prosthesis is attached to the limb, i.e. with a prosthetic socket on a stump or with an orthotic splint at the extremity of a sound hand. Therefore, a direct examination on prostheses users may be necessary to confirm that this result applies to them as well. Importantly, the experimental setup presented in this study can be used with minimal changes for individuals with upper limb amputation.

Finally, the approach shown in this work can be applied in realms other than upper-limb prosthetics; for instance, to drive rehabilitation or assistive devices for patients of musculoskeletal degenerative conditions. Stroke survivors, for instance, might benefit from a faster data acquisition procedure, when engaged in rehabilitation procedures involving complex robotic devices. Rehabilitation based upon Virtual Reality is also a target for this procedure [27]. Robotic control based upon muscle activity can be also transferred to teleoperated scenarios [28]. In future work we aim to explore the use and feasibility of the procedure described in this paper in some of these scenarios.

IV. Conclusions

To address the limb position effect in myocontrol, we have investigated a dynamic alternative to the common acquisition procedure that covers multiple static positions. In this dynamic variant, the users moved their hands with constant speed through multiple positions while maintaining a given grasp. We have evaluated both the static and dynamic procedures in a highly realistic prosthetic setting, in which users performed challenging activities of daily living that required bimanual coordination. Our results with fourteen able-bodied subjects show that the two procedures yielded similar performance in terms of total completion time, but that the dynamic acquisition procedure was faster and less tiring for the users. This indicates that the dynamic procedure should be preferred over the static one when trying to counter the limb position effect.

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References

[1] P. Parker, K. Englehart, and B. Hudgins, "Control of powered upper limb prostheses," *Electromyography: physiology, engineering, and noninvasive applications*, pp. 453–475, 2004.

[2] CoApt Engineering, Inc., "*Complete Control*," www.coaptengineering.com/technology.html.

[3] J. Vogel, C. Castellini, and P. van der Smagt, "EMG-based teleoperation and manipulation with the DLR LWR-III," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2011, pp. 672–678.

[4] N. Ho, K. Tong, X. Hu, K. Fung, X. Wei, W. Rong, and E. Susanto, "An EMG-driven exoskeleton hand robotic training device on chronic stroke subjects: task training system for stroke rehabilitation," in *IEEE International Conference on Rehabilitation Robotics (ICORR)*. IEEE, 2011, pp. 1–5.

[5] I. Vujaklija, D. Farina, and O. C. Aszmann, "New developments in prosthetic arm systems," *Orthopedic Research and Reviews*, vol. 8, pp. 31–39, 2016.

[6] A. Fougner, E. Scheme, A. D. Chan, K. Englehart, and Ø. Stavdahl, "Resolving the limb position effect in myoelectric pattern recognition," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 19, no. 6, pp. 644–651, 2011.

[7] E. Scheme, K. Biron, and K. Englehart, "Improving myoelectric pattern recognition positional robustness using advanced training protocols," in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE, 2011, pp. 4828–4831.

[8] L. Peng, Z. Hou, Y. Chen, W. Wang, L. Tong, and P. Li, "Combined use of sEMG and accelerometer in hand motion classification considering forearm rotation," in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2013, pp. 4227–4230.

[9] N. Jiang, S. Muceli, B. Graimann, and D. Farina, "Effect of arm position on the prediction of kinematics from EMG in amputees," *Medical & biological engineering & computing*, vol. 51, no. 1-2, pp. 143–151, 2013.

[10] A. Radmand, E. Scheme, and K. Englehart, "A characterization of the effect of limb position on EMG features to guide the development of effective prosthetic control schemes," in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE, 2014, pp. 662–667.

[11] R. N. Khushaba, A. Al-Timemy, S. Kodagoda, and K. Nazarpour, "Combined influence of forearm orientation and muscular contraction on EMG pattern recognition," *Expert Systems with Applications*, vol. 61, pp. 154–161, 2016.

[12] J. L. Betthauser, C. L. Hunt, L. E. Osborn, M. R. Masters, G. Lévay, R. R. Kaliki, and N. V. Thakor, "Limb position tolerant pattern recognition for myoelectric prosthesis control with adaptive sparse representations from extreme learning," *IEEE Transactions on Biomedical Engineering*, vol. 65, no. 4, pp. 770–778, 2018.

[13] D. Farina, N. Jiang, H. Rehbaum, A. Holobar, B. Graimann, H. Dietl, and O. C. Aszmann, "The extraction of neural information from the surface emg for the control of upper-limb prostheses: emerging avenues and challenges," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 22, no. 4, pp. 797–809, 2014.

[14] D. Yang, W. Yang, Q. Huang, and H. Liu, "Classification of multiple finger motions during dynamic upper limb movements," *IEEE journal of biomedical and health informatics*, vol. 21, no. 1, pp. 134–141, 2017.

[15] N. Jiang, I. Vujaklija, H. Rehbaum, B. Graimann, and D. Farina, "Is accurate mapping of EMG signals on kinematics needed for precise online myoelectric control?" *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 22, no. 3, pp. 549–558, 2014.

[16] M. Ortiz-Catalan, F. Rouhani, R. Brånemark, and B. Håkansson, "Offline accuracy: a potentially misleading metric in myoelectric pattern recognition for prosthetic control," in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE, 2015, pp. 1140–1143.

[17] A. Chadwell, L. Kenney, M. Granat, S. Thies, J. Head, A. Galpin, R. Baker, and J. Kulkarni, "Upper limb activity in myoelectric prosthesis users is biased towards the intact limb and appears unrelated to goal-directed task performance," *Scientific reports*, vol. 8, no. 1, p. 11084, 2018.

[18] Thalmic Labs, Inc., "*Myo* bracelet," www.thalmic.com, no longer available for sale.

[19] Touch Bionics by Össur, "*i-LIMB Revolution* prosthetic hand," www.touchbionics.com/products/active-prostheses/i-limb-ultra.

[20] A. Rahimi and B. Recht, "Uniform approximation of functions with random bases," in *Allerton Conference on Communication Control and Computing (Allerton08)*, Sep. 2008, pp. 555–561.

[21] A. Gijsberts, R. Bohra, D. Sierra González, A. Werner, M. Nowak, B. Caputo, M. A. Roa, and C. Castellini, "Stable myoelectric control of a hand prosthesis using non-linear incremental learning," *Frontiers in neurorobotics*, vol. 8, p. 8, 2014.

[22] I. Strazzulla, M. Nowak, M. Controzzi, C. Cipriani, and C. Castellini, "Online bimanual manipulation using surface electromyography and incremental learning," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, no. 3, pp. 227–234, 2017.

[23] S. Wang, J. Hsu, L. Trent, T. Ryan, N. Kearns, E. Civillico, and K. Kontson, "Evaluation of performance-based outcome measures for the upper limb: a comprehensive narrative review," *PM&R*, 2018.

[24] L. M. Hermansson, A. G. Fisher, B. Bernspång, and A.-C. Eliasson, "Assessment of capacity for myoelectric control: a new Rasch-built measure of prosthetic hand control," *Journal of rehabilitation medicine*, vol. 37, no. 3, pp. 166–71, 2005.

[25] P. J. Kyberd, A. Murgia, M. Gasson, T. Tjerks, C. Metcalf, P. H. Chappell, K. Warwick, S. E. Lawson, and T. Barnhill, "Case studies to demonstrate the range of applications of the Southampton Hand Assessment Procedure," *British Journal of Occupational Therapy*, vol. 72, no. 5, pp. 212–218, 2009.

[26] C. Schuster, S. Hahn, and T. Ettlin, "Objectively-assessed outcome measures: a translation and cross-cultural adaptation procedure applied to the Chedoke McMaster Arm and Hand Activity Inventory (CAHAI)," *BMC medical research methodology*, vol. 10, no. 1, p. 106, 2010.

[27] C. Nissler, M. Nowak, M. Connan, S. Büttner, J. Vogel, I. Kossyk, Z. Marton, and C. Castellini, "VITA - An everyday virtual reality setup for prosthetics and upper-limb rehabilitation," *Journal of Neural Engineering*, vol. 16, no. 2, 3 2019.

[28] O. Porges, M. Connan, B. Henze, A. Gigli, C. Castellini, and M. A. Roa, "A wearable, ultralight interface for bimanual teleoperation of a compliant, whole-body-controlled humanoid robot," in *Proceedings of ICRA - International Conference on Robotics and Automation*, 2019, in press.