A PORTABLE PROPORTIONAL CONTROL PROSTHESIS WITH HIGH-RESOLUTION DATA LOGGING

Mark Brinton[1], Elliott Barcikowski[2], Tyler Davis[3], Michael Paskett[1], Jacob George[1], Gregory Clark[1]

1. Biomedical Engineering, University of Utah, Salt Lake City, UT, USA; 2. Ripple Neuro LLC, Salt Lake City, UT, USA; 3. Neurosurgery, University of Utah, Salt Lake City, UT, USA.

ABSTRACT

This paper describes a portable, prosthetic control system that uses a modified Kalman filter to provide 6 degree-of-freedom, real-time, proportional control. We describe (a) how the system trains motor decoding algorithms and controls an advanced bionic arm, and (b) the system's ability to record an unprecedented and comprehensive dataset of EMG, hand positions and force sensor values. This technology enables at-home dexterous bionic arm use, and provides a high-temporal resolution record of daily use—essential information to determine clinical relevance and advance future research.

INTRODUCTION

Commercially available prostheses suffer from a variety of limitations, including: a limited number of pre-determined grips, temporal delay due to sequential inputs used to select grips, fixed output force (e.g., from classifier algorithms), extensive training that takes days to weeks, and non-intuitive methods of control (e.g., inertial measurement units on arm or feet) [1]–[3]. Advanced control of multiple degrees-of-freedom, and the training associated with them, are not always amenable to deployment on portable systems with limited computational power. However, a Kalman filter [4], modified with non-linear, ad-hoc adjustments [5], [6], can provide a computationally efficient approach to proportionally and independently control multi-degree-of-freedom prostheses.

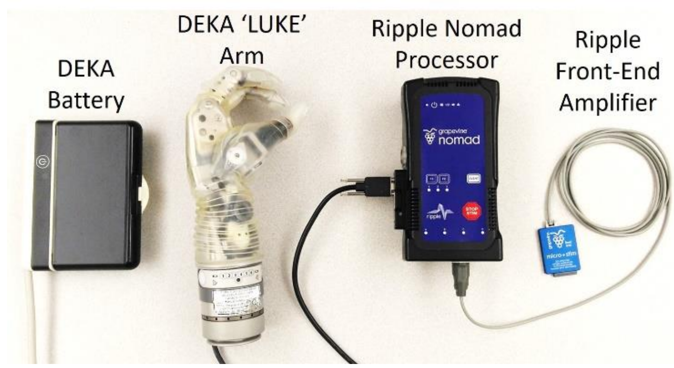

Figure 1 – Portable take-home system includes the DEKA LUKE Arm and battery, the Ripple Nomad neural interface processor and battery (hidden) and a front-end amplifier (amplifier for surface EMG shown here).

In a previous publication we demonstrated supervised at-home use of a portable, prosthetic control system that relied on a modified Kalman filter to provide 6 degree-of-freedom, real-time, proportional control [6]. Here, we describe this system including: (a) how it can be used to train motor decoding algorithms and control an advanced bionic arm; and (b) its ability to record an unprecedented dataset of electromyography (EMG), hand positions and force sensor values. This technology constitutes an important step toward the commercialization of dexterous bionic arms by demonstrating at-home use of proportional control, multi-degree-of-freedom prostheses and recording high-temporal resolution data describing the arm use.

METHODS

Design Considerations

A portable take-home system designed to research advanced bionic arms should meet several criteria for optimal performance and data collection: (a) the system must accurately and efficiently control the prosthetic arm; (b) training of the prosthetic arm must not be too long or burdensome to prevent its daily use; (c) high temporal resolution data should be stored automatically so that researchers can study at-home use without influencing the users with in-person observation; and (d) the system must be easy to use and allow the user to adjust control preferences.

Hardware and Signal Acquisition

The components of the portable system are shown in Figure 1, including: (a) the 6 degree-of-freedom DEKA LUKE Arm (Manchester, NH) and its 13 force sensors (0 to 25.5 N) and rechargeable battery; (b) the Nomad Neural Interface Processor (Ripple Neuro, Salt Lake City, UT) with a more than 4-hour, rechargeable battery, a 500 GB disk storage and up to 512 channels of data acquisition; and (c) the front-end amplifier (Ripple Neuro, Salt Lake City, UT) which filters (15 to 375 Hz bandpass; 60/120/180 Hz notch) and amplifies 1-kHz sampled EMG data. Surface EMG in intact participants was recorded with a Micro + Stim front-end, and implanted EMG in the amputee participant was recorded with an active gator front end. Ripple also provided firmware with the Nomad for data acquisition (EMG at 1 kHz; LUKE Arm positions and force sensors at 33 Hz), communication with the LUKE Arm (CAN bus protocol), ability to start and stop compiled decoding algorithms via external buttons, and WiFi communication to interface with external devices. The Nomad runs Linux 8 (jessie) environment with an Intel® Celeron™ processor (CPU N2930) at 1.83 GHz with 2 GB RAM. Algorithms were converted to C using MATLAB® Coder and compiled for stand-alone use on the portable Nomad.

Table 1: Computational times required for training and testing (running) the steady-state, modified Kalman filter.

Process	Computation Time
Training:	
Data collection	252 s
Channel Selection	198 s
Train Steady State Kalman Filter	0.7 s
Total Time	7.5 min
Testing:	
Update Positions	< 1 ms

Training, Feature Calculation and Motor Decoding

The Kalman filter presented by Wu et. al [4] was modified with external, ad-hoc thresholds as described in George et. al [6]. To improve stability and reduce the effort required to sustain grasping movements, a latching filter was also applied to the output of the modified Kalman filter [5]. Training the modified Kalman filter first requires the user to mimic a computer-controlled prosthetic arm as it cycles through several movement trials for each degree-of-freedom. Features were then calculated for each differential EMG pair (496 total from 32 single-ended electrodes) by taking the mean-absolute value of a moving 300-ms window. Using the movement kinematics and the EMG features, the compiled algorithm recursively chose the 48 most-descriptive features using the Gram-Schmidt forward selection algorithm [7] and then trained the Kalman filter matrices [4].

Human Subjects

Eight EMG leads (Ripple Neuro LLC; Salt Lake City, Utah, USA) with 4 contacts each, and a ninth lead with an electrical reference and ground, were implanted in the lower-arm extensor and flexor muscles of a trans-radial amputee as described elsewhere [6]. Intact individuals used the portable system with a bypass socket [8] and a custom-made neoprene sleeve with 32 surface EMG electrodes, plus 1 reference and 1 ground (George et al., MEC, 2020). All experiments and procedures were performed with approval from the University of Utah Institutional Review Board.

RESULTS

Three external buttons were employed to create a simple user-friendly interface. Pressing the first button initiated a new training session. The second button initiated a previously trained and compiled motor decoding algorithm so that the user could have on-demand control of the arm. A third button was used to toggle between position or velocity control modes or to freeze a degree-of-freedom at a desired position.

Figure 2 - Two-handed activities-of-daily living in the home using a bypass socket and the portable system: (a) using scissors, (b) donning a sock and (c) folding a towel.

The system was trained in about 7.5 minutes—including a movement mimicry session (252 sec) and the subsequent selection of the optimal channels and computation of the steady-state Kalman filter matrices (about 199 sec) (Table 1). Training data included 4 trials for each of the thumb, index, middle/ring/little and wrist flexion and extension; thumb adduction and abduction; wrist pronation and supination; and grasping and extending all digits together. The trained Kalman filter was automatically saved to a log file and could be recompiled onto the Nomad as a stand-alone application for on-demand use (e.g., the second external button). This was accomplished over the Nomad's wireless network using a laptop and required less than 30 seconds.

Prior to use, the steady-state Kalman gain matrix (K) was calculated by iteratively running the filter until the fluctuations in every value of the gain matrix were less than 1x10^{-6}, reaching steady state after about 25 ms. With the gain (K), the observation (H) and the state-transition (A) matrices, a steady state matrix (Γ) was then calculated:

$$\Gamma = \mathrm{A} - \mathrm{K} * \mathrm{H} * \mathrm{A} \qquad (1)$$

Thus, new position predictions ($\hat{x}$) were calculated with only two matrix multiplications involving the previous positions and the 48 selected EMG features (z):

$$\hat{x}_{new} = \Gamma * \hat{x}_{previous} + \mathrm{K} * \mathrm{z} \qquad (2)$$

This simplification avoided a computationally expensive matrix inversion required by the recursive algorithm. Consequently, the time required to predict new positions and update the prosthesis was, on average, less than 1 ms, far below the update loop speed of 33 ms (see Table 1). The portable system was used at home to perform two-handed tasks with both intact participants (Fig. 2) and a trans-radial amputee [6].

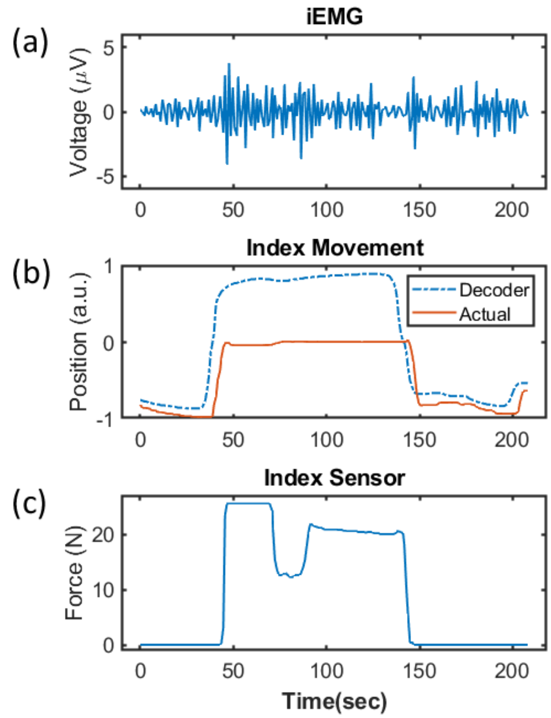

Figure 3 - (a) A differential implanted EMG channel (iEMG, at 1 kHz), (b) motor decoding algorithm estimates and actual arm positions (at 30 Hz) and (c) force sensor values (at 30 Hz) recorded while a trans-radial amputee grasped, held and released an orange.

Comprehensive EMG (sampled at 1 kHz), arm positions and arm forces (both sampled at 30 Hz) were stored on the Nomad while a trans-radial amputee grasped, held and released an orange (Figure 3). Figure 3 shows one differential pair of the implanted EMG (iEMG) and the index finger positions and force. A grasp occurred when the index position moved from -1 to +1. During the grasp, the difference in position between the motor decoding algorithm's estimated and the actual positions occur because the object prevents the finger from flexing to its full extent (Fig. 3b). This caused a dramatic increase in force (Fig. 3c). Data from the 32 EMG channels, 6 arm positions and 13 force sensors are saved at a rate of 250 MB/hour in an '.hd5' format. As a result, the 500 GB capacity of the Nomad can record nearly 2000 hours of arm use.

DISCUSSION

We have shown that a modified Kalman filter can be trained in about 7.5 minutes to proportionally control 6 independent degrees-of-freedom using the Nomad portable processor. The portable system has been used in the lab and at home by intact persons, as well as by a trans-radial amputee to perform tasks not possible with his commercial prosthesis [6]. Even with an ordinary microprocessor, position updates were generated much faster than the 33-ms loop speed, providing the users with real-time control. The portable system also stores EMG, position and force data with unprecedented temporal resolution. This comprehensive dataset will be crucial for fully understanding how proportional control algorithms are used during unsupervised at-home use.

Figure 3 highlights how the comprehensive data recorded by the Nomad reveals complex interactions between the various degrees of freedom for improved control. The stable index finger position implies that the amputee held the orange with a fixed grasp from pick up to release; however, the force data revealed a dip in force during this same period. Close inspection of the position data of the opposing thumb (not shown) also shows that a subtle readjustment occurred to improve the grasp stability. Because degrees of freedom are coupled together during object manipulation, the connection between each degree of freedom must be considered. Due to complex regional pain syndrome, the trans-radial amputee in this study had kinesiophobia and had not used his hand for several years prior to amputation. As a result, the recorded EMG signals were often very weak (Figure 3a). However, with these weak signals, the portable system and motor decoding algorithms still provided the participant the functional control necessary to complete common daily tasks in his own home.

Rich datasets like this will help researchers study at-home, unsupervised prosthesis use; improve motor decoding algorithms and training paradigms [9] by understanding the types of grasps and degrees of freedom commonly used; understand when mastery of prosthetic control occurs and when interventions might be applied or lifted; better describe noise encountered in real-world environments and design features and algorithms that reduce its influence on motor performance; and address many other unanswered questions about at-home use of advanced upper-limb prostheses. These rich datasets will also enable future at-home trials to study the benefits and use of high-resolution sensory feedback from intraneural electrical stimulation—a feature soon to be added to the portable system.

The most computationally demanding aspect of training was performing Gram-Schmidt forward selection to choose the 48 most useful features out of the 496 differential pairs. Despite taking considerable time up front, this down-selection method has several advantages [7]. First, choosing the features up-front enables fast loop speeds (below 33 ms) by eliminating the need to calculate complex features (e.g., principal components) or even all 496 differential EMG features during each update cycle. Second, forward selection recursively chooses independent and informative features using orthogonality reduction and correlation with the training kinematics. This ensures that each selected feature describes kinematics and not uncorrelated noise. Refined movements, the hallmark of proportional control algorithms, account for little variance and could be inadvertently discarded using techniques agnostic to the training kinematics. Finally, orthogonalization in the forward selection algorithm avoids redundant features and singularities.

A key feature of the portable system is that the time from powering the system to having real-time proportional control is less than 8 minutes. The amount of time required to both collect training data by mimicking arm movements and train the motor decoding algorithm are related to the number of trials for each mimicked movement. In this work, and published elsewhere, an amputee familiar with the training process only trained with 4 trials on each degree-of-freedom and a grasp and extension of all digits. With this training, he was able to control the arm in the lab and perform tasks not possible with his commercial prosthesis at home [6]. A less experienced user may require training with more trials; however, even if a naïve user requires twice as many trials the total training time (mimicry and computation) is still under 15 minutes.

In its current form, the portable system is only able to communicate over a CAN bus python socket with the DEKA LUKE Arm. However, other custom communication sockets could be designed to communicate through the micro D-sub, USB or Bluetooth connections available to Nomad for proportional control of and data logging from other prosthetic limbs.

In the future, the portable system will also include sensory stimulation for haptic feedback in response to the forces experienced by the prosthesis. Ultimately, this system will be used in upcoming take-home clinical trials to record high-resolution data and study advanced, proportional control algorithms and sensorized prostheses in trans-radial amputees.

ACKNOWLEDGEMENTS

This work was sponsored by the Hand Proprioception and Touch Interfaces (HAPTIX) program (No. N66001-15-C-4017; BTO, DARPA). We thank Ripple Neuro, LLC for their generous support with custom firmware that enabled many features including high-resolution data collection and storage on the Nomad. We acknowledge Dr. Douglas Hutchinson and Dr. Christopher Duncan for their clinical support with the amputee participant.

REFERENCES

[1] A. D. Roche, H. Rehbaum, D. Farina, and O. C. Aszmann, "Prosthetic Myoelectric Control Strategies: A Clinical Perspective," *Curr. Surg. Reports*, vol. 2, no. 3, 2014.

[2] L. J. Resnik *et al.*, "EMG pattern recognition compared to foot control of the DEKA Arm," *PLoS One*, vol. 13, no. 10, p. e0204854, Oct. 2018.

[3] E. Biddiss and T. Chau, "Upper limb prosthesis use and abandonment: A survey of the last 25 years," *Prosthet. Orthot. Int.*, vol. 31, no. 3, pp. 236–257, 2007.

[4] W. Wu, Y. Gao, E. Bienenstock, J. P. Donoghue, and M. J. Black, "Bayesian population decoding of motor cortical activity using a Kalman filter," *Neural Comput.*, vol. 18, no. 1, pp. 80–118, 2006.

[5] J. G. Nieveen, M. R. Brinton, G. A. Clark, D. J. Warren, and V. J. Mathews, "A Non-Linear Latching Filter to Remove Jitter from Myoelectric and Peripheral Neural Interface Movement Estimates for Prosthetics," *Press*.

[6] J. A. George, T. S. Davis, M. R. Brinton, and G. A. Clark, "Intuitive neuromyoelectric control of a dexterous bionic arm using a modified Kalman filter," *J. Neurosci. Methods*, vol. 330, p. 108462, Aug. 2019.

[7] J. Nieveen, D. Warren, S. Wendelken, T. Davis, D. Kluger, and D. Page, "Channel Selection of Neural And Electromyographic Signals for Decoding of Motor Intent," *Myoelectric Control. Conf.*, p. 720, 2017.

[8] M. D. Paskett *et al.*, "A Modular Transradial Bypass Socket for Surface Myoelectric Prosthetic Control in Non- Amputees," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. PP, no. c, p. 1, 2019.

[9] J. A. George, M. R. Brinton, C. C. Duncan, D. T. Hutchinson, and G. A. Clark, "Improved Training Paradigms and Motor-decode Algorithms: Results from Intact Individuals and a Recent Transradial Amputee with Prior Complex Regional Pain Syndrome," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2018, vol. 2018-July, pp. 3782–3787.