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CLINICALLY PRACTICAL APPLICATIONS OF PATTERN RECOGNITION FOR MYOELECTRIC PROSTHESES

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ABSTRACT

The promise of pattern recognition for improved control of upper-extremity powered prostheses has existed for a long time. During the years of offline research and algorithm development, very little experience has been gained with real-time use in clinical and chronic settings. Our group, having the benefit of working with subjects who have undergone targeted muscle reinnervation (TMR) surgery, is at the forefront of real-world application of pattern recognition for upper extremity amputees. Based on our experiences, we highlight a progression of myoelectric control schemes from conventional control to enhanced pattern recognition control, stressing the application of simple pattern recognition schemes to replace more conventional control. These clinically practical pattern recognition systems incorporate a realistic number of electrodes and the ability to control available prosthetic components. Our experience suggests how the impending, and initial deployment of pattern recognition-controlled prostheses for daily use can be more approachable than what is depicted in high-dimension studies common in the literature today.

BACKGROUND

The use of pattern recognition for robust myoelectric control, and its promise for improved prosthesis function, has been steadily investigated since the 1960s [1-20]. Investigators around the world have developed techniques and demonstrated efficacy for systems involving anywhere from one [7, 10, 16] to hundreds [8, 15, 19] of electrodes and controlling few [2, 5, 11, 13, 18] to multiple [3, 8, 12] classes of motion. Near exhaustive studies of each algorithmic component of myoelectric pattern recognition have been and continue to be conducted, as researchers investigate the effects of different approaches to data windowing [3, 10], feature types [2-4, 10], classifier types [1, 4, 9], post-processing [3], and so on. With exceptions in most recent history [8, 20], the majority of these studies have been conducted offline, using recorded data, and have often used able-bodied research subjects as substitutes for amputees. In the meantime, clinical application of myoelectric control has persisted with 'direct' (or 'conventional') control techniques, limiting the ease with which powered prosthesis users can function. It is the authors' view that it is a valid time for pattern recognition to be incorporated into the clinical standard for myoelectric prosthesis control. We suggest that the overwhelming amount of information and results from scientific studies of pattern recognition may be well suited to researchers but not necessarily to the clinicians who are ultimately responsible for facilitating the marriage of pattern recognition to everyday prostheses.

Direct Control

The synonymous terms 'direct control' and 'conventional control' have recently been introduced to characterize the forms of myoelectric control that do not include pattern recognition. Many configurations of direct control are clinical standards, including various strategies using the signal amplitude from one or two muscle sites (myosites) and/or coupled with switches, buttons, etc. [21]. Clinicians strive to use strategies of direct control that are simple (to ensure user-acceptance) yet maximize function. Although these schemes are seen as reliable and robust, perhaps because they are the best we have, the function of a powered device under direct control is limited to the amount and type of control information a user can reliably present to the control system. That barrier has held R&D of device hardware to a limited pace for a number of years [22]. Recent activity in neural control mechanisms such as targeted muscle reinnervation (TMR) [23] is helping to surpass that bottleneck and fuel development of advanced powered prosthetics. Although pattern recognition has been proposed as a viable control mechanism to command these advanced (more degrees of freedom, etc.) devices, it is discussed here how pattern recognition should first benefit today's devices with a few electrodes and a small number of powered degrees of freedom.

Pattern Recognition

Proponents of pattern recognition speak of its potential for controlling multiple degrees of freedom and of how well it aligns with a future generation of powered devices. These promises are usually presented at the cost of using more myosites than the clinical norm (two for agonist/antagonist control). Many challenges exist for implementing a large number of electrodes and commercially available components for additional degrees of freedom are only beginning to become available. Microprocessor hardware capable of pattern recognition has not yet been developed onto any commercially available platforms. When these microprocessors arrive, the first true clinical implementations of pattern-recognition-controlled prostheses can be realized. It is suggested that basic setups be introduced first; that is, pattern recognition as a seamless sequential substitute for single or dual site direct control, commanding commercially available components that prosthetists are comfortable using.

PATTERN RECOGNITION: SUBSTITUTE FOR DIRECT CONTROL

The example shown here compares a clinicians' setup of direct control to pattern recognition control using the same two antagonistic myosites, intending to operate a terminal device with powered open and close. For this demonstration, two myosites were located on an able-bodied subject by means of palpation for hand open and close (augmented with wrist extension and flexion); see Figure 1(a). In clinical practice considerable time is often also spent with an aide such as a MyoBoy[1] to help prosthetists determine ideal sites. Using custom software, ACE[2], dual-site control for hand open and close was set-up; a clinician iteratively adjusted input gains and activation thresholds for each channel while instructing the subject to open and close their hand. For the second part of the demonstration, ACE was used to separately configure the pattern recognition control for the same degree of freedom. For this, the subject was prompted to conduct two 3-second contractions of hand open and close; ACE recorded the muscle signals for these two classes along with periods of no movement, constructed an internal pattern classifier, and automatically configured the dual-site set-up. What is important to note are not the specifics of the experimental setup, rather the procedural differences when replicating a direct control set-up with pattern recognition.

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[1] Otto Bock HealthCare, Vienna, Austria
[2] Acquisition and Configuration Environment (ACE) is a clinician interface software suite developed at UNB IBME. Additional information about ACE can be found within these proceedings.

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Of equal or greater importance, it can be shown that pattern recognition can provide a much ‘cleaner’ separation of command signals for cases of substantial myosite crosstalk (involuntary co-activation of muscles). As shown in the top row of Figure 1(b), signals from both myosites are apparent as the subject attempts to open or close the hand. This can be commonplace in current clinical practice and means the clinician must spend considerable time and effort training the user and adjusting signal gains and thresholds to achieve acceptable control. The bottom row of Figure 1(b) highlights how the signals become mutually exclusive with pattern recognition, simplifying the setup for the clinician. A short, supplemental video[3] shows the real-time direct control system (highlighting the challenge of crosstalk interference) and can be compared to the supplemental video[4] showing the real-time pattern recognition setup.

Three points can be made in support of pattern recognition substitution for direct control: (1) pattern recognition can be less susceptible to initial placement of electrodes; (2) the cumbersome (and time consuming) prosthetist process of setting gains and thresholds is replaced by a semi-automated training regimen, and, perhaps most applicable to clinicians; (3) signals affected by a large degree of crosstalk or interference can be made more distinct and useable.

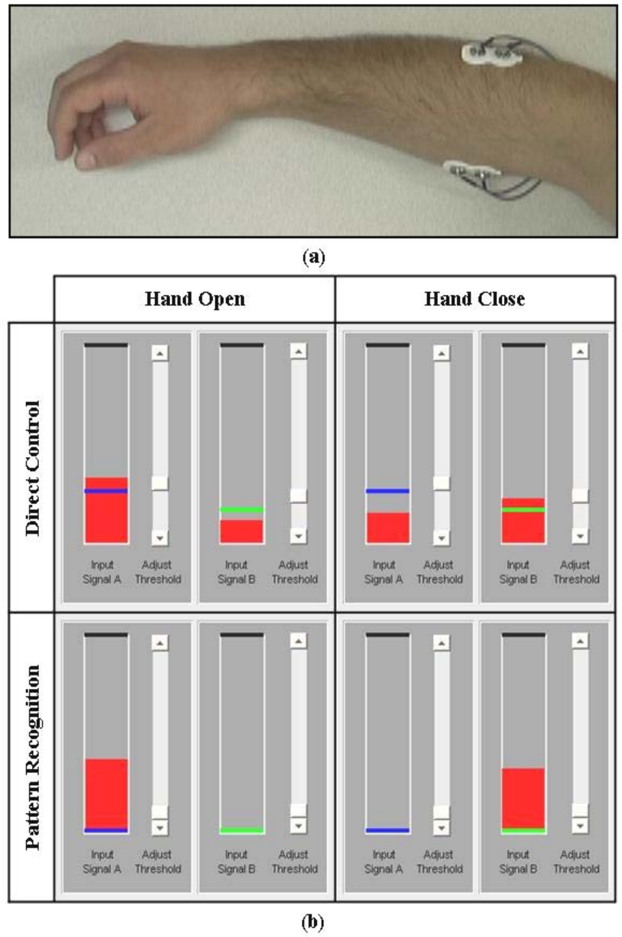

Figure 1: *(a) Two myosite setup used for this demonstration; (b) Table of screen captures showing the challenge for gain and threshold selection by prosthetists using direct control (top row) and how pattern recognition can simplify setup of the same system (bottom row). (screenshots used with permission from UNB)*

PATTERN RECOGNITION: ADDING FUNCTIONALITY

Considering a prosthesis with two powered degrees of freedom (e.g. powered terminal device and wrist rotator), prosthetists must be creative with the use of external harness switches, co-contractions, fast/hard vs. slow/soft strategies, etc in order to have the device function under direct control from one or two myosites. Pattern recognition provides the potential to eliminate switching in the control system as it can decipher between the [hand open, hand close, wrist pronate, and wrist supinate] intentions of the user in a more intuitive and natural way.

Expanding on the example from above, pattern recognition was used to show enhanced functionality while using the same two myosites. The able-bodied subject performed a training session where two 3-second contractions were recorded for each of five classes: hand open, hand close, wrist flexion, wrist extension, and no motion. The complete data acquisition and classifier

[3] www.smpp.northwestern.edu/kuiken/necal_videos/2site_2motion_Direct_Control.wmv
[4] www.smpp.northwestern.edu/kuiken/necal_videos/2site_2motion_Pattern_Recognition.wmv

preparation session took approximately 1 minute. For exploration, the subject controlled a virtual prosthesis in real-time. The actual session can be seen in a supplemental video[5]. Immediately obvious is the ability to control wrist and hand functions using two myosites without the need for switching. Also, as before, clinician setup time is moved from adjustment of gains, thresholds, and switching parameters to helping guide the subject through a pattern recognition training session.

What is demonstrated here is a simple expansion of a basic case. Consider this concept a building block leading to even greater device functionality. As a prosthetist becomes more comfortable in fittings using more than one or two electrodes, pattern recognition performance will be enhanced as more myoelectric information is introduced to the system [3]. Additional myoelectric information suggests the potential to control even more degrees of freedom [8, 19].

PATTERN RECOGNITION WITH TMR SUBJECTS

Most subjects with targeted muscle reinnervation (TMR), a novel surgical technique that provides the residual muscles of amputees with neural information native to the amputated limb [23], have been fit with powered prostheses for take-home use. These semi-advanced devices have used three and four (six in one known case) myosites in place of the one or two that are customary without the surgical benefit. None of these devices employ pattern recognition; instead, prosthetists have creatively expanded on common direct control methods. Although function has improved for these shoulder disarticulation [24, 25] and transhumeral [26] amputees, the availability of pattern recognition may provide even greater benefit.

We have examined data taken from four TMR patients with the intent to demonstrate the efficacy of pattern recognition in three tasks: as a substitute of their current direct control setup, as a system controlling additional devices using the current myosites, and as a fully enhanced system controlling additional devices using additional myosites. Each subject participated in the study with informed consent approved by the Northwestern University Institutional Review Board. Electrodes were placed at predetermined locations on TMR subjects based on clinical practice (first four myosites copied their direct control prosthesis) and input from a prior study involving a high-density electrode array [8]. Using ACE, subjects were randomly prompted to hold muscle contractions for ten classes of movement for 4-seconds each, separated by 3-seconds of rest. In total, 16 seconds of data per class were recorded for pattern classifier training and 16 seconds of data were set aside for testing. Testing a classifier offline yields a measure of classification accuracy which is not a measure of, but believed to be related to, pattern recognition functionality [27, 28].

The results within Table 1 highlight a progression from direct control to enhanced control using pattern recognition. Classification accuracies in the cases where pattern recognition substitutes the direct control setup are relatively high, suggesting the subjects would function well with the motions and myosites of their take-home prosthesis and would have more intuitive control as switching or using external inputs is unnecessary. Adding four more natural motions, while maintaining direct control myosites, yields slightly lower classification accuracies that are still reasonable [3]. By adding four additional myosites, the classification accuracies return to near original levels where function was more limited. The authors advocate that all accuracies presented are clinically practical starting points for each subject and would only improve with additional subject and classifier training. The reader is encouraged to draw their own conclusions

[5] www.smpp.northwestern.edu/kuiken/necal_videos/2site_4motion_Pattern_Recognition_with_VR.wmv

on simple pattern recognition substitutions of direct control and on pattern recognition for advanced control, based on their own clinical experiences with direct control.

	% classification accuracy			
	SD-A	SD-B	TH-A	TH-B
Direct Control Setup 4 myosites: (1)EF, (2)EE, (3)HO, (4)HC (WP, WS by other†)	n/a	n/a	n/a	n/a
Pattern Recognition substituting Direct Control 4 myosites: EF, EE, WP, WS, HO, HC	94.5	97.1	87.3	91.6
Enhanced Pattern Recognition (more motions) 4 myosites: EF, EE, WP, WS, WF, WE, HO, 3grasps	84.0	80.1	72.8	80.9
Enhanced Pattern Recognition (more motions and myosites) 8 myosites: EF, EE, WP, WS, WF, WE, HO, 3grasps	95.1	88.2	85.4	89.2

†WP,WS controlled by: (SD-A) HO, HC myosites, switched by touch pad at shoulder OR co-contraction; (SD-B) 2 touch pads at shoulder, and; (TH-A and TH-B) linear transducer in harness.

Table 1: *Classification accuracies for the three pattern recognition cases and depicts the functional differences by subject. EF = elbow flexion, EE = elbow extension, WP = wrist pronation, WS = wrist supination, WF = wrist flexion, WE = wrist extension, HO = hand open, HC = hand close*

CONCLUDING REMARKS

The impending introduction of pattern recognition control to powered prostheses should not be intimidating; even if much of the published work on pattern recognition considers many myosites and many motions. In a clinically practical setup of pattern recognition, a prosthetist can benefit from ‘cleaner’ signals, less switching concerns, and the potential to help their patients achieve more intuitive control of more powered degrees of freedom.

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