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Special Lecture

Novel Control Strategies for Arm Prostheses : A Partnership between Man and Machine*1

Patrick M Pilarski,*2 Ann L Edwards,*2 K Ming Chan*2,*3

State-of-the-Art Myoelectric Prostheses

The human hand is an exquisite instrument. Most importantly, it is capable of performing a wide range of functions, and is able to switch seamlessly from one function to the next in response to the changing environment. Not surprisingly, the hand's loss through amputation is a major disability with drastic impact on quality of life. Prosthetic devices are designed to help alleviate some of the negative consequences of hand and arm amputation. Early prosthetic devices were purely mechanical, as exemplified by the traditional hook-and-cable systems. Later prostheses began to incorporate electrical and mechanical components to perform functions, and could be controlled by muscle signals in an amputee's residual limb (**Fig. 1**).

Termed *myoelectric control*, the use of muscle signals for control of robotic prostheses has gained increasing popularity since the 1960's.[1,2] Recent technological advances in sensor and actuator technology have further enabled the development of sophisticated myoelectric prostheses. These advances include myoelectric hands with multiple functions, or grip patterns, that amputees can select to perform various tasks.[3] For example, a number of commercially available artificial hands allow users to select and control grip patterns such as the active index finger or tripod grip. Though not yet commercially widespread, some research-focused myoelectric hands also possess the capability to be embedded with sensors to provide motion or touch feedback, both to the user and to the hand itself. In a display of technological prowess, the most advanced prosthetic limbs systems have over 20 joints and numerous sensors that convey information about touch, temperature, and motion. An example of an advanced limb system is the Modular Prosthetic Limb (MPL) pioneered at the Johns Hopkins Applied Physics Laboratory.[4,5]

Limitations and Biological Solutions

When controlled by an able-bodied (non-amputee) subject, the movement of next-generation limbs systems like the MPL can begin to replicate the motion of a biological limb. Unfortunately, a major constraint that leads to marked degradation of performance is the limited number of intuitive myoelectric signals that can be used to control those myoelectric prostheses, especially in amputees with proximal limb loss. These barriers have severely limited the accessibility and usability of existing and emerging myoelectric technologies.[2,3,6,7]

The loss of intuitive myoelectric control signals has been addressed, at least in part, by the introduction of the targeted muscle reinnervation procedure pioneered by Kuiken et al.[8,9] By re-routing and reinnervating the residual stump muscles using the median, ulnar and radial nerves, the amputees are able to produce appropriate myoelectric signals to move the prosthesis with much less effort. However, with the increasingly sophisticated prostheses that offer the possibility of discrete arm and hand movements, the mismatch between that and the number of possible electromyography (EMG) control sites on their residual limb becomes particularly critical (**Fig. 2**). This seriously hinders an amputee's ability to use their prostheses to their fullest potential.

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*2 Division of Physical Medicine and Rehabilitation, Department of Medicine, University of Alberta, 5-005 Katz Group Centre, University of Alberta, Edmonton, Alberta, Canada, T6G 2E1

*3 E-mail : ming.chan@ualberta.ca

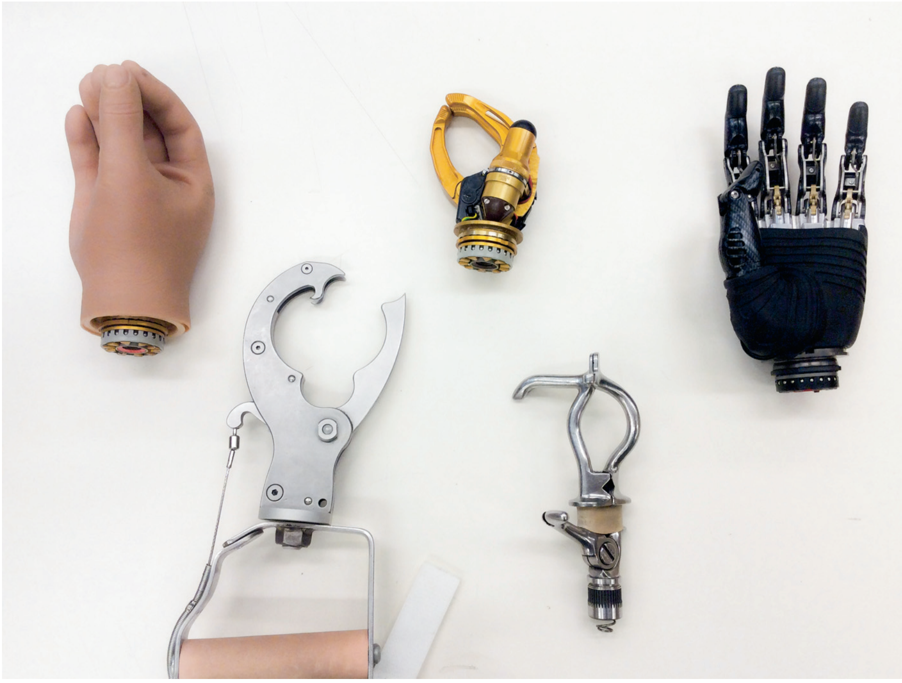

Fig. 1 Examples of currently available prosthetic hands.
Body-powered terminal devices and myoelectric hands interpret muscle signals from a patient's body to actuate battery-powered robotic motors.

Potential Technological Solutions

While the biological approaches have reached an impasse, interface design and engineering represents perhaps the most common means of increasing commercial prosthesis functionality and addressing patient concerns about the difficulty of device control. For example, one simple solution used in several commercial prosthetic hands and arms requires the user of a myoelectric arm to toggle sequentially through the different functions or grip patterns of their device, akin to having to switch through a list of alphabet characters one-by-one in order to spell a single word on a cellular phone. No matter how well designed, this is often painfully slow and unintuitive.

Pattern Recognition for Better Prosthesis Control

Pattern recognition is an alternative approach to conventional myoelectric control, and is currently considered to be the new gold standard in performing sequential multi-joint prosthesis control.[6] Pattern recognition techniques use a type of machine learning that maps an amputee's EMG signals to one of the functions of a prosthetic system. It exploits the fact that different combinations of muscle contractions made by the person as they attempt to perform a motor sequence yield unique patterns of EMG signals. For example, when a subject attempts to perform a pinch grip, the EMG pattern measured from their body varies from that of the pattern generated when they attempt to open their hand (depicted for the case of a chest-reinnervated TMR subject in **Fig. 3**).

While pattern recognition relies on statistical machine learning techniques that have been developed over the course of decades, its operation in high-level terms is straightforward (Fig. 3). For example, when an amputee is instructed by the machine to perform elbow flexion, the pattern of EMG activity recorded by the control system will be associated with the target motion. The process is then repeated for every other motion the user wants to perform with the prosthetic limb. In essence, the prosthesis has to memorize the patterns corresponding to each of the user's desired movements.

Compared to conventional myoelectric control, where signals are manually mapped to target motions, pattern recognition provides a much more flexible, user-train-

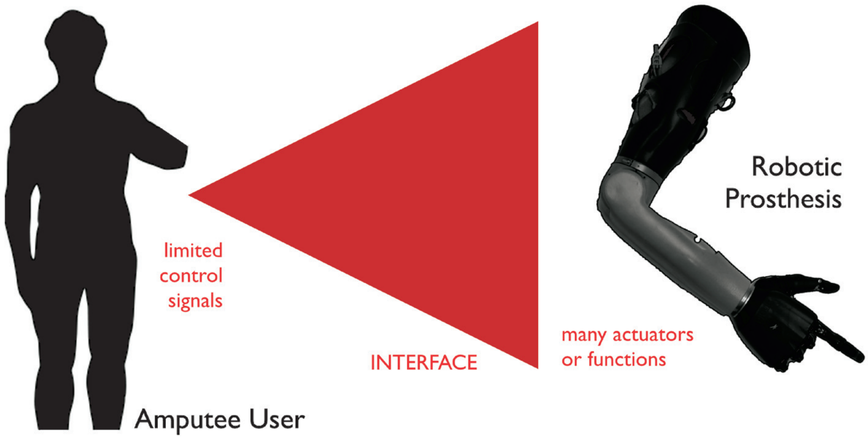

Fig. 2 The mapping of control signals from an amputee's body to the motor functions of a robotic prosthesis.

This mapping often involves determining a user's intent from a small number of signals and using them to control an increasing number of joints or movements.

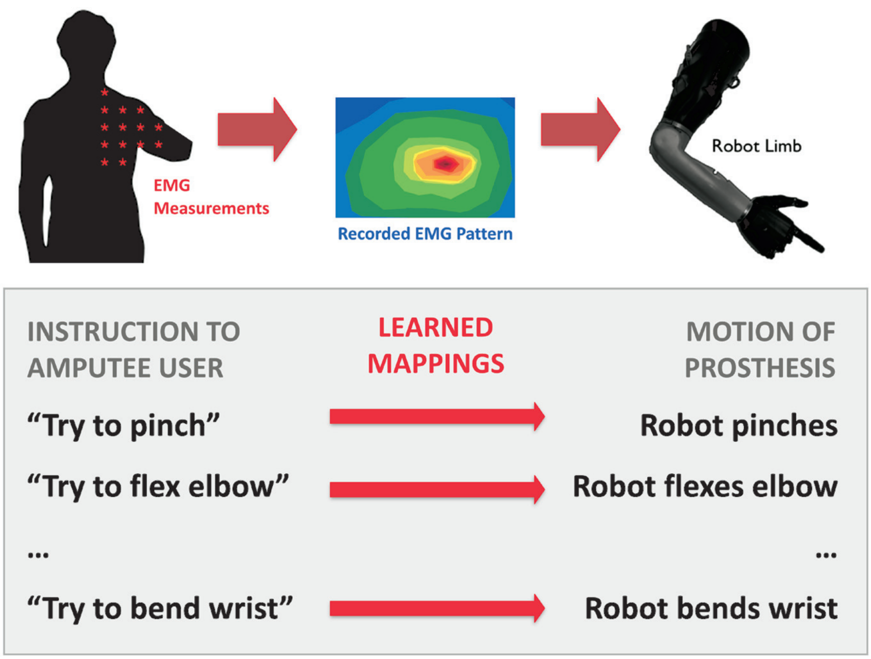

Fig. 3 Operation of pattern recognition.

Patterns of myoelectric signals are sampled from a user as they are instructed to complete a series of motions or grasps. Machine learning is used to form mappings between the recorded EMG patterns and the desired movement of the actuators of the patient's robotic prosthesis. When the device next sees a given pattern, it will perform the corresponding movement.

able control approach that increases both the intuitive nature of control and also the number of functions that are sequentially accessible to the user. However, pattern recognition in its current form has a number of known limitations. First, functions of the prosthesis must be controlled sequentially. Only one type of motion is available at a time, and the system is not capable of natural, multi-joint motions. Second, like conventional myoelectric control, pattern recognition systems remain sensitive to errors. As electrodes shift, muscles fatigue, and the person's limb moves in different orientations, the system has to be retrained periodically. While this retraining process can be brief when compared to recalibrating a conventional EMG controller, it nevertheless requires a break in the continuous operation of an amputee's device. The literature acknowledges the need for systems to adapt to changing circumstances.[6,10]

New Opportunities through Real-time Machine Learning

Because of the aforementioned limitations of many prosthesis control techniques, enhancements to existing solutions alone is likely insufficient for better control. The limitations of current solutions become more glaring when considering amputees with very proximal arm amputations—i.e., patients who have few EMG control sites but require the full multitude of functions that will be present in next-generation prostheses (as depicted in Fig. 2). Innovative new control strategies will be crucial to bridging this rift between signals and function. With the advent of rapidly increasing computing power and the miniaturization of electronics, we are for the first time presented with the opportunity for implementing machine learning algorithms and on-board controllers to share the burden of simultaneous multi-joint control. Notably, increased computing power and new computing methods promise the ability to develop a prosthetic arm that is also the perfect assistant—prostheses capable of learning about and adapting to their user's needs during continued use.

Such ongoing learning by the prosthesis is a form of real-time machine learning. By building up a relationship with a user that is based on learned sensorimotor knowledge (i.e., expectations about how the user and their prosthesis will interact), a limb controller can potentially improve and adapt over time to enhance the user's control experience.[11,12] In real-time machine learning, machine intelligence is used to learn about and adapt to user-specific situations that may be challenging or even impossible for the users to overcome on their own. Using these learned details as a basis for modulating control, an amputee user can be presented with a clear and consistent interface that promotes rapid training and proficient use of the myoelectric prosthesis.

Real-time machine learning therefore may provide an answer to some of the current problems faced by users of advanced prosthetics. The task of understanding biofeedback signals from the human body is often complex—the difference between waving at someone, picking up a cup, and doing the dishes is significant, and manually designing control systems as task needs increase in complexity can be demanding or even impossible. Real-time machine learning has the capacity to incrementally acquire an understanding of a patient's needs and patterns of use during ongoing activity, and promises to then help translate a patient's intentions into prosthesis control commands during complex real-life tasks. Furthermore, many details about the way a prosthesis will be used are unknown at the time a patient is fitted with a device in the clinic. Although a user may be able to specify their desired goals or outcomes, how they must control their prosthetic device to achieve their goals is often unclear. Better educating control systems via learned knowledge about a user that is gathered by the device over extended periods of time can help to circumvent problems that arise after initial prosthetic fitting. Put differently, ongoing machine learning allows a device and a user to co-adapt—a device can continue to improve and streamline control interfaces for a user outside of the clinic.[13–15] A further complication lies in the fact that the world and the user's life are constantly changing, and thus systems like modern prosthetic arms must adapt to these changes. Such adaptation is possible with real-time machine learning.

A practical example of applying real-time machine learning to prosthetic arms is through the implementation of adaptive switching, as described by Edwards et al.[14] During adaptive switching, the machine can learn to predict, based on contextual factors such as the arm's current position and speed, which prosthetic function a user intends to use next—e.g., elbow flexion, hand opening, or wrist extension—and when they intend to switch to that next motion or function. From preliminary results,[13,14] it appears that adaptive switching requires the participant manually toggle the modes of their prosthesis much less often and much faster than when using a conventional approach without persistent machine learning. Real-time machine learning allows a device to give the user what they want, and when they want it, in a way that matches with their current situation, needs, and environment.

Conclusions and Perspectives

While current prosthetic devices and control methods have greatly improved life for amputees, future work is needed to create artificial limbs that match and exceed the potential of an amputee's lost biological limb. Important avenues for research and development include methods for allowing simultaneous, multi-joint movements, effective motor synergies, and dexterity that approximates that of a biological limb. Natural feedback is also needed to transmit feelings of touch, heat, kinesthesia, and other sensation from the limb to the human user. Biological constraints in the number and quality of signals that can be measured non-invasively from the body further restrict the use of powerful new prosthetic technology by patients, and new surgical techniques like TMR are helping provide innovative options in this regard. With respect to what is being currently used by patients, although conventional control devices are still the mainstay of clinical prescription, they have limitations. Pattern recognition offers profound improvements over conventional control. While seeing initial commercial use, enhancements to pattern recognition ideas are ongoing. Real-time machine learning is complementary to pattern recognition and conventional control, and is a natural next step to enhance and/or supersede pattern recognition, allowing prostheses to adapt to patients' needs. Importantly, real-time machine learning is a technology that promotes unique, ubiquitous, intelligent rehabilitation devices. Preliminary evidence suggests that we can create prosthesis control methods that are situated and enhanced by ongoing activity, improved through interactions with real-life situations, and that can adapt as a patient progresses in their recovery and use of a their rehabilitation technology. Machine learning enables the development of contextual control. Furthermore, by allowing an artificial-limb controller to continually learn and adapt over time, it may be possible to make clinical training and at-home practice effort more synergistic and efficient. The ideas described in this paper therefore hold the promise of building a true partnership between an amputee user and their next-generation prosthesis.

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