

Myoelectric Control of Artificial Limbs— Is There a Need to Change Focus?

Recently, there have been several media reports on advanced multifunction upper limb prostheses, often hyped as “the mind-controlled artificial hands” [1]. Advanced signal processing of the electromyogram (EMG) signal and innovative surgical procedures, such as the targeted muscle reinnervation (TMR) and targeted sensory reinnervation (TSR), are the driving forces behind these achievements. Nonetheless, despite the enthusiasm of some public presentations of artificial devices, there still exist considerable challenges before these developments can be beneficial to the general amputee population. In this article, the basic concept of myoelectric control and the state of the art in both industry and academia will be presented. It will emerge that there is a gap between industrial and academic achievements and that this gap will continue to expand unless a change of focus in systems for myoelectric control occurs.

EMG AND MYOELECTRIC CONTROL

The electrical manifestation of the muscle contractions is called EMG, and it contains information about the neural signals sent from the spinal cord to control the muscles. The power of the EMG is partly correlated to the intensity of the motor neural drive to the target muscle [2]. This property has been exploited in many applications, including myoelectric-controlled prosthesis, where the surface EMG is recorded from the remnant muscles of the stump and used, after processing, for activating cer-

tain prosthetic functions of the prosthesis, such as hand open/close. Although such control of prosthetic functions is possible through signals other than the EMG (e.g., brain or nerve signals), the surface EMG has been virtually the only control signal for practical uses of multifunction upper limb prosthesis since the 1950s. This status is due to its easy access and is likely to remain in the

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foreseeable future. Moreover, TMR currently allows to selectively transfer some of the nerves that once controlled the amputated limb to some surrogate muscles which act as biological amplifiers of the nerve activities. Similarly, TSR allows sensory receptors in the skin near or over TSR site to relay sensory information as if they were the receptors in the amputated limb. In this view, the muscle interface becomes a very general man-machine interface that in principle can be used even when the level of amputation is high.

Despite decades of research and development, however, myoelectric control of upper limb prostheses still generates relatively limited clinical (and commercial) impact, as only one out of four upper limb amputees chose to use myoelectric-controlled prostheses [3]. This situation is contrasted by the increasing enthusiasm on this topic within the academic community,

which has shown for several years that gestures and motor tasks can be classified very accurately by the analysis of the EMG. This article aims at highlighting this gap between the academic and industry state of the art in myoelectric control. We focus on the main challenges facing myoelectric control and on possible approaches to bridge the gap.

CONVENTIONAL MYOELECTRIC CONTROL

The earliest versions of the myoelectric controller are dated to the 1950s and 1960s and employed simple algorithms. For example, a function could be activated by comparing the EMG amplitude to a threshold and different functions could be controlled by the same technique applied to multiple recording sites. Despite dating back to more than 50 years ago, this simple approach is still used by the vast majority of commercially available powered prostheses. Nevertheless, these systems are inherently limited and the number of reliable functions per channel never exceeds three [4].

PATTERN CLASSIFICATION-BASED MYOCONTROL

Since the early 1960s, pattern recognition-based classification techniques started to attract the interest of the research community working on controlling artificial limbs. The pattern classification approach for myoelectric control is based on the assumption that there exist distinguishable and repeatable signal patterns among

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different types of muscular activations. A pattern classification myoelectric controller usually consists of three main steps: segmentation, feature extraction, and classification. Segmentation is usually performed in the intervals of 150–200 ms to obtain an acceptable control delay. Feature extraction and classification of the EMG have been performed in many ways in the scientific literature. It is now accepted that among the large number of possible combinations of features and classifiers, the combination of time domain features with Fisher linear discriminant analysis provides a good balance between algorithm performance and computational efficiency. For example, with such an approach, Englehart et al. reported >95% real-time classification accuracy in a four-class wrist contraction experiment [5]. Further improvements can be achieved by additional processing steps, such as majority vote or feature dimensionality reduction.

THE DICHOTOMY BETWEEN ACADEMIA AND INDUSTRY STATE OF THE ART

Interestingly, all myoelectric controllers based on pattern classification that have appeared in the literature since the 1990s have provided similar performance (>90% classification accuracy). Further refinement of such accuracy levels seems thus not strictly needed. Moreover, a comprehensive study of the performance and usability of 36 myoelectric controllers demonstrated that the relation between classification accuracy and usability of the controller is absent or very weak at best [6]. This further diminishes the importance in advancing accuracy in classic pattern classification for myocontrol. From the scientific literature, one would conclude that the myoelectric classification for prosthetic control is not only possible but also highly accurate, even with a large number of functions (>10). This conclusion heavily collides with the clinical practice and commercial data: amplitude-based myoelectric control (and not pattern classification) is used

in all commercial devices and only a quarter of patients with an upper limb amputation use a myoelectric prosthesis [3]. The pattern classification approach of myoelectric control seems thus very successful in scientific papers but much less for the patients. The reasons for this dichotomy, which will be analyzed in the following, highlight the need for a change of focus in signal processing algorithms for myoelectric control.

CHALLENGES IN SIGNAL PROCESSING AND FUTURE DIRECTIONS

SEQUENTIAL AND ON/OFF CONTROL: HOW FAR CAN IT GO?

The main problem with the pattern classification for myoelectric control is that it inherently leads to a control scheme that is substantially different

A PATTERN CLASSIFICATION MYOELECTRIC CONTROLLER USUALLY CONSISTS OF THREE MAIN STEPS: SEGMENTATION, FEATURE EXTRACTION, AND CLASSIFICATION.

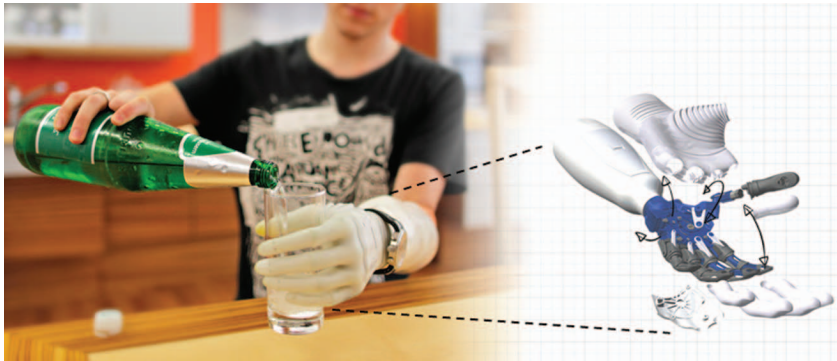
from the natural control. Natural movements are continuous and require the coordination of multiple physiological degrees of freedom (DOF) across several joints. Natural movements of the limb are usually simultaneous and proportional articulations of these DOFs. Therefore, the parameter space that describes natural movements (EMG, kinematics, and kinetics) is continuous. On the other hand, the number of patterns in a pattern classification-based controller is limited. Thus, a crude discrete approximation of the continuous parameter space is obtained by classification. This discrete approximation leads to two problems. First, only one class can be selected in one decision, i.e., the controller is sequential. Indeed, none of the pattern classification-based methods currently proposed in the literature can generate reliable simultane-

ous activation of two classes. Second, proportional control is not directly obtained from the classification. Actually, proportionality in the commands impairs the accuracy of the classification. The features of a particular pattern migrate in the feature space as the intensity of the movements varies and they may pass through the decision boundaries, which leads to erroneous decisions. Proportional control is currently implemented after the classification decisions are made, by taking the average power across all channels, which is an ad hoc approach.

The above discussion underlines the need for the development of methods that realize simultaneous and proportional control of multiple DOFs. This research direction has been attempted very recently in “biologically inspired” approaches where the multichannel EMG signals are factorized to extract “motor commands” of higher functional level with respect to the individual muscle activations [7]. This approach has been followed in recent subsequent studies that proved the feasibility of a more intuitive and advanced control of artificial limbs.

SENSORY-MOTOR INTEGRATION: THE NEED FOR CLOSING THE LOOP

Sensory-motor integration is a process ubiquitous to the physiological human motor control. Motor commands, formed by a neural controller, generate purposeful movements (e.g., reaching, grasping), and the resulting sensory consequences are fed back to the controller via a multimodal sensory feedback (e.g., vision, proprioception, touch/pressure). Importantly, the operation of this sensory-motor loop is essential for effective motor control, learning, and adaptation. Multimodal sensory feedback is so relevant for motor control that the functional movements of patients who are deprived of sensory feedback are severely impaired and require significant mental effort, although there is a full integrity of the motor pathways [8]. Despite the awareness of the need for sensory feedback in normal task performance, most current myoelectric



[FIG1] Otto Bock's Michelangelo hand, providing 2 + 2 DOFs of the wrist and hand. (Photo reprinted with permission from Otto Bock and MXR Productions.)

prostheses implement only the feed-forward or motor part of the loop while the sensory feedback is limited to a single modality (vision).

The concept of artificial sensory feedback in prosthetics was conceived a long time ago [9]. The main motivation for this pioneering research was to improve the utility of simple devices that were available at the time by providing the user with the means to operate the prosthesis in a closed loop. Contrary to those simple, one-DOF mechanisms, modern prosthetic hands, such as the Otto Bock Michelangelo hand (shown in Figure 1) or Touch Bionics i-Limb, are highly sophisticated robotic systems with a number of independently controllable DOFs. In this case, the sensory feedback is no longer just an optional add-on, but it is likely an essential element that has to be implemented for users to master a complex device and operate it without an excessive mental effort. However, the research on sensory integration in myoelectric control in the last decades has been negligible when compared to the resources devoted to decoding motor actions.

The feed-forward information properties of electrocutaneous and vibratory stimulation channels have been extensively studied in the past [10]. However, the loop has not been fully closed to evaluate the performance of these displays for the closed-loop control of dynamic systems. In addition to these system control experiments, the role and operation of physiological multimodal sensory feedback and its components during reaching and grasping should be

better understood. In other words, the biological sensor fusion algorithms need to be decoded at a sufficient level of detail so that the main principles can be integrated when designing artificial feedback systems. Such decoding could be accomplished by the sensor fusion

GIVEN THE DIFFICULTY OF ROBUST CONTROL SOLELY BY USING EMG, THE USE OF OTHER SENSOR MODALITIES SEEMS NECESSARY FOR THE CONTROL OF COMPLEX DEVICES.

approach that is currently being investigated in neuroscience, e.g., combining electroencephalography and functional magnetic resonance imaging for better understanding of neural information processing [11]. Finally, the introduction of the feedback will unavoidably influence the feed-forward part. Therefore, an effective solution to the issue of delivering feedback to the prosthesis' user would open new perspectives in algorithm design and new possibilities for effective and intuitive prosthetic control.

ADAPTATION

Most of the studies on myoelectric control algorithms are being performed in controlled laboratory conditions with intact-limbed subjects, in fixed arm/trunk positions. These conditions do not present the sources of artifacts that are com-

mon in more practical scenarios. Moreover, the statistical properties of the EMG recorded in classic myoelectric control paradigms in laboratories are usually stationary, which are different from more general conditions. It is known that the EMG signal characteristics change because of sweat, fatigue, displacement of the recording electrodes, or from different strategies adopted by the user who is adapting to the system. The fact that very few myoelectric control systems proposed in the scientific literature can adapt to such changes is by itself a good reason for the lack of usability of these systems in practice. Adaptive signal processing of EMG signals for myoelectric control is thus another imperative demand (e.g., [12]), in particular we envision similar efforts as coadaptivity between human and the control strategy as implemented recently in other rehabilitation technologies (e.g., [13]). As for the other demands that we have listed above, the efforts in this direction are currently very limited.

MORE IS BETTER: SENSOR-FUSION APPROACH

Given the difficulty of robust control solely by using EMG, the use of other sensor modalities seems necessary for the control of complex devices. The rich multimodal input would not only allow for the improved control but could also lead to the development of intelligent controllers that are able to operate somewhat autonomously, thereby taking over some of the burden from the user. Miniature sensors and embedded systems with considerable processing power are currently available so that this approach is both feasible and practical. For example, inertial measurement units can measure the orientation and movement of the prosthesis and from this, the intention of the user and the phase of the reaching movement could be predicted, complementing the information obtained via a myoelectric interface. Recently, a system demonstrating a combination of artificial vision, ultrasound distance sensor, and myoelectric control has been presented [14]. The next steps in this direction should be the implementation of

sensor-fusion approaches, in which inertial, myoelectric, and possibly other information sources (e.g., artificial vision) are integrated. This requires data fusion and signal processing algorithms to predict user intentions and control reaching and grasping movements based on a multimodal feedback.

SUMMARY AND CONCLUSIONS

Myoelectric control has a great potential for improving the quality of life of persons with limb deficiency. However, despite the tremendous success in obtaining almost perfect classification accuracy from EMG, its clinical and commercial impact is still limited. We have identified some of the reasons that we believe are relevant for explaining this seeming contradiction. The majority of current pattern classification methods do not provide simultaneous and proportional control, are not implemented with sensory feedback, do not adapt to the changes in EMG signal characteristics, and do not integrate other sensor modalities to allow complex actions. These problems hinder the possibility of using such paradigm in applications that aim at clinical and commercial use. Academic research has focused in the past decades on refining classification accuracy and has relegated to secondary importance the aspects outlined in this article. As such, a gap between the academia and the industry state of the art has been generated unnecessarily. This gap could be filled by addressing the specific needs of intuitive myoelectric control and system robustness. With this position, we are not questioning the need of further research within pattern classification of EMG. Indeed, three of the four demands that we have identified can be implemented within a pattern classification paradigm. Rather, our intention is to raise the awareness for the necessity of additional parallel research efforts toward issues whose importance for

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practical implementations has been underestimated.

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