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Clinical Perspectives in Upper Limb Prostheses: An Update

Aidan D. Roche[1,4] · Ben Lakey[2] · Irene Mendez[2] · Ivan Vujaklija[2] · Dario Farina[2] · Oskar C. Aszmann[3]

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Abstract
Purpose of Review This paper aims to summarise the development trends in upper limb bionics over the past 5 years.
Recent Findings Increasingly pattern recognition and regression control algorithms are being used to decode EMG signals for prosthetic control and are moving towards clinically available devices. Additionally, bionic reconstruction has built on the principles of targeted muscle reinnervation to add another rung to the reconstructive ladder for upper limb deficits. Finally, novel methods to provide sensation to prostheses are trialled not just in the laboratory but in home testing systems as well.
Summary Engineering, surgical and rehabilitation methods are gradually adding more capabilities to modern prostheses, moving towards the goal of replicating natural hand function.

Keywords Bionic reconstruction · Upper limb amputation · Neural interfaces · Motor control · Sensory feedback · Prosthetic design

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✉ Aidan D. Roche
aidan.roche@nhs.net

1 Department of Plastic & Reconstructive Surgery, Sheffield Teaching Hospitals NHS Foundation Trust, Sheffield, UK

2 Department of Bioengineering, Imperial College London, London, UK

3 Centre for Extremity Reconstruction, Medical University of Vienna, Vienna, Austria

4 ECAT, The University of Edinburgh, Edinburgh EH16 4TJ, UK

Introduction

Returning hand function to upper limb amputees continues to be a challenging problem. The history of upper limb prosthetic development since the early 20th century has been outlined previously in this journal [1]. Engineers and medical doctors have continued an iterative approach to advancing prosthetic performance, with the best outcomes coming from projects where there is a conjoined approach.

This update paper aims to outline the progress that has been made particularly in the last 5 years by providing insights of the evolution of well-known control approaches in their translation to the clinical environment, describing developments in attachment of prostheses to the stump, highlighting advances in surgical techniques and rehabilitation while introducing future research directions in the field.

Refining the Control Algorithms

Traditional approaches, such as direct control, record the activity of antagonist remnant muscles above the amputation with pairs of electrodes, and map their amplitude to the force or speed of distinct prosthetic movements (prosthesis degrees of freedom, DOFs). This paradigm has been extended to multiple DOFs based on different switching approaches, such as muscle co-contraction or physical buttons [2], to map these muscles' activity into multiple DOFs. Pattern recognition was later applied to provide more natural transitions between movements. It assumes that each motion produces a global, distinct and repeatable activity pattern that can be recorded with multiple electrodes [3]. Based on these patterns, the system sequentially detects a discrete movement from a predefined set. However, simultaneous movements can also be attained by either using parallel architectures or including the combined movements in the training set [4]. In addition, a post-processing step has been proposed to normalise the velocity of the prosthesis to the motion-specific dynamic range of the signal amplitude and accordingly establish proportional control within a pattern recognition-based system [5]. More recently, regression-based algorithms, such as Linear Regression (LR) [6] and Nonnegative Matrix Factorization (NMF) [7], proved to be a simple and promising approach to provide proportional and simultaneous control of multiple DOFs. These algorithms create a continuous mapping between the signals' amplitude and the control space of the different DOFs (Fig. 1.).

Until recently, one relevant limitation in the development of pattern recognition methods for myocontrol was their testing mainly performed offline. It is now established that high offline accuracy is misleading since it does not necessarily translate in accurate functional control of a physical prosthesis. In this regard, several recent studies have addressed the discrepancy between offline and online lab performance metrics [8–11], evidencing the benefits of virtual reality feedback and real-time subject's adaptation. Real-world studies validated the novel control algorithms with amputees wearing prostheses, and performing clinical tests that mimic daily tasks [12]. Although they are not ideal, the Box and Blocks test (B&B), the Clothes Pin Relocation Test (CPRT), the Southampton Hand Assessment Protocol (SHAP) or the Assessment of Capacity for Myoelectric Control (ACMC) provide a more accurate assessment of the impact of research outcomes in the real world than virtual tasks.

Yet, only a few studies have been published on the clinical validation of pattern recognition [13–17]. One of most relevant of these studies was performed on eight targeted muscle reinnervation (TMR) transhumeral amputees and compared proportional pattern recognition and direct control before and after a home trial [16]. Results showed that there was significantly better performance in SHAP and CPRT when using pattern recognition, participants improved their pattern recognition control with time and that pattern recognition was the participants' qualitatively preferred method after the trial. Similar results were obtained in a home trial with three transradial amputees [15]. These and other promising results resulted in the very recent commercial development of Myo Plus by Ottobock [18], which is the second pattern recognition controller in the prosthetic industry after that produced by Coapt [19].

Alternatively, regression-based research has focused on improving LR and NMF algorithms [20–22], and validating their online performance in virtual tasks with able-bodied subjects [9] and amputees [7]. In addition, research studies have assessed their robustness to the number of electrodes and location [23], signal non-stationarities [11] and donning/doffing [24]. The robustness of regression-based approaches poses an advantage over pattern recognition, which requires frequent recalibration [15, 16]. Finally, the performance and robustness of LR and two direct control approaches using B&B and CPRT were compared in five end users (amputees and congenital) during clinical tests [24]. Results showed that overall, LR outperformed direct control with high robustness to donning/doffing but less to arm position (although comparable to direct control). Nevertheless, regression-based algorithms currently fail to provide reliable control over more than 2 DOF [25], and often produce undesired interferences when single DOF are active [26]. These drawbacks are likely the reason why there are no regression-based prostheses commercially available yet.

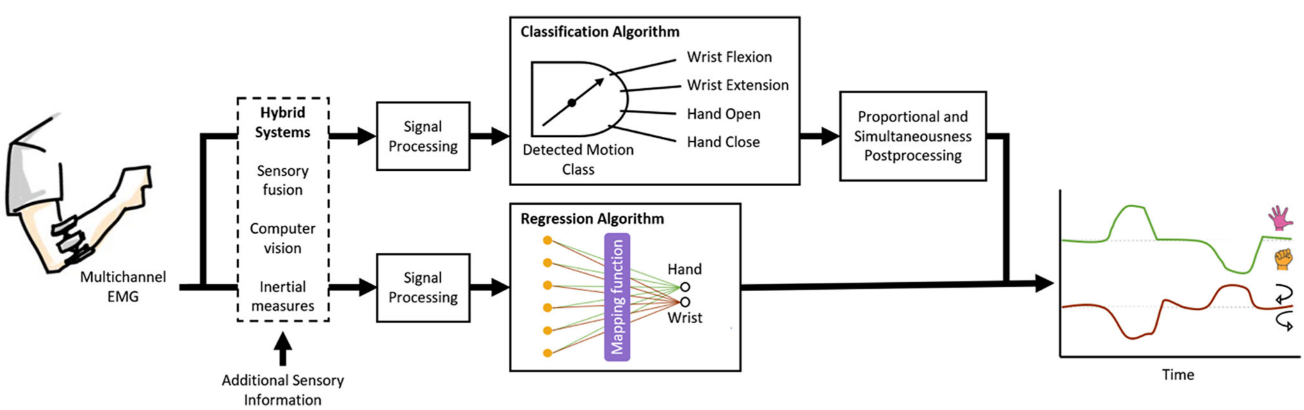

Fig. 1 Summary of the most clinically advanced myoelectric approaches: classification (pattern recognition), regression algorithms, and hybrid systems. Recent post-processing steps have provided classification systems means for proportional and simultaneous control, which is directly generated by regression-based systems. Sensory fusion and computer vision have also been combined with these approaches to improve their performance

Alternative hybrid systems with additional information sources have also been suggested to improve myoelectric control [27, 28]. For instance, pattern recognition attained better performance in a custom functional task when EMG features and inertial measurements were combined in one transradial amputee [29]. Furthermore, it has been shown that when dealing with complex dexterous tasks amputees can achieve significantly better performance once provided with a sensory-fusion and computer vision-enhanced EMG control system [30]. Although these systems can be integrated in physical prostheses, further clinical validation is still required.

A very recent and emerging control approach that is gaining some interest in the research community is the direct decoding of neural information from surface EMG [27, 31, 32]. Decomposition algorithms separate the motor unit action potential waveforms and the timing of their occurrence from the EMG interference signal. The timings of these action potentials, modelled as spike trains, provide information about the neural drive to the muscles, and thus represent a fine source of movement intention. It has lately been shown that the motor unit spike trains obtained after decomposition in dynamic motor tasks are accurate, consistent and discriminative, proving their suitability as sources of control [33]. The concept has been proven through a series of offline experiments with TMR patients using pattern recognition, direct control and a musculoskeletal modelling, where motor unit spike trains attained a superior performance than conventional EMG features [34]. The main limitation of this approach is the offline execution of the decomposition algorithms [35–38]. However, the feasibility of real-time decomposition has been demonstrated [39]. Hence, the next milestone of this approach is the validation of these results in a real-time control task [33, 34].

Adapting Prostheses for Comfortable Control

Prosthetists have traditionally adapted reverse plaster-casted sockets to accommodate myoelectric electrodes by cutting holes over the most appropriate recording site. However, when the stump changes in size and shape, the socket has to be redesigned to allow for repositioning of electrodes. Gel-based electrodes can be placed directly onto the skin, obviating the need to redesign the socket, but have been known to induce skin irritation [40] and are generally impractical for day-to-day use. Electrodes directly incorporated into roll-on liners to form smart fabrics have been developed to secure stable and constant skin contact for signal recording, reducing the need for changes in socket structure [41]. Greater suspension and range of motion are possible with roll-on-sleeves that position electrode sites in a repeatable way [42].

Armbands with integrated EMG recording sites made out of these smart fabrics have been demonstrated to enable versatile myoelectric control (Fig. 2) [43]. The most notable benefits of fabric electrodes are the breathable and comfortable application on a washable and foldable interface resulting in decreased irritation to the user's skin [40, 44]. A home usage review of a silver-coated stretch fabric with embedded electrodes by patients found that the combination of materials did not disrupt the necessary structural properties of the liner [45]. Further developing these fabrics, high-density EMG (HD-EMG) recording systems have been designed to simplify daily repositioning of the electrodes by the user [46].

Alongside innovations in the lining of sockets, 3D printing technologies have been developed with the aim of reducing printing time and material costs during socket manufacture. Using a combination of three-dimensional scanning and computer modelling, tailored made prostheses can be designed for individual patients [47]. 3D scanning allows for a permanent digital record of the changing residual limb geometry over time, allowing for identification of pressure points or optimal electrode placement, hence refining the socket for a more comfortable and functional fit [48]. In addition, this manufacturing technique allows for simple replacement parts and repairs to be completed in a cost-effective way while allowing personalisation of the colour, shape and size of the device [49, 50]. Importantly, prosthetists still maintain control over the manufacture of the socket using computer-aided design interfaces.

While it has been estimated that 3D printing may reduce the direct manufacturing and material costs of sockets by nearly two-thirds [47, 51], the cost of designing, assembling and fitting the limbs may decrease the overall affordability [52]. In a recent review of 58 3D-printed hands for differing amputation levels, the technology

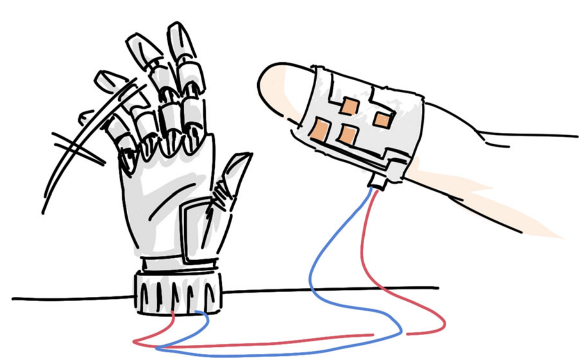

Fig. 2 Armbands with integrated EMG recording sites made out of smart fabrics for myoelectric control (Adapted from Brown et al.) [43]

demonstrated its potential for individualisation, but has not yet been rigorously tested to confirm its overall function and durability, which inevitably will affect user acceptance [50].

While the lack of evidence for functional capacity of 3D-printed hands at present may prevent widespread uptake in adult patients, the most promising application is with children who have congenital limb deficiencies or amputations. Due to a child's mental and physical growth and development rates [49], as well as socio-economical background, traditional prostheses are less accessible to children [51]. Promising devices, such as Open Bionics' Hero Arm [50], have gained attention, not only because of their approval through the US Food and Drug Administration, and trials within the UK's National Health Service, but also because of the novel use of popular science fiction characters to engage children and increase uptake [51].

Advancements in Surgical Techniques

TMR is now an established technique for surgeons who specialise in reconstructing upper limb loss [16, 53]. TMR's use of selective nerve transfers to hyperinnervate, and thus change the neurological landscape of remaining musculature has been proven to be an effective technique in controlling prostheses in high-level amputations (transhumeral and shoulder disarticulation). Bionic reconstruction has built on the TMR technique to utilise free functioning muscle transfers, by not only transferring nerves but useable muscles to increase the functional EMG signals available for prosthetic control [54]. The bionic reconstruction technique enables patients who have non-functioning and insensate hands to be electively amputated in favour of a prosthetic hand after lower root brachial plexus injuries or critical soft tissue injuries [55, 56]. Both of these surgical procedures are gaining grounds outside of the two main research hospitals where they were developed, providing more treatment options for amputees globally (Fig. 3).

While these procedures continue to be refined through clinical practice, other research concepts are edging their way towards clinical trials. The interface between man and machine can be viewed as the rate-limiting step in prosthetic control. Although both TMR and bionic reconstruction provide gross information on muscle contraction, enough to control up to seven simultaneous functions in clinical practice, this is far from natural control. Recent peripheral nerve quantification studies have shown that there are 350,000 axons supplying the human arm [57]. These axons convey vast quantities of both motor and sensory information that are being missed by current methods.

Attempts to interface directly with peripheral nerves have provided useful information in the laboratory setting [58–61], but concerns over long-term tissue degradation and resulting loss of useable signal quality have prevented their long-term implantation [62]. A novel method to harness individual peripheral nerve activity is to culture myoblasts directly onto the ends of transected nerves. Together with a scaffold containing an electroconductive polymer, these regenerative peripheral nerve interfaces (RPNI) aim to increase the amount of discrete signals available for prosthetic control [63]. In a way, RPNIs can be viewed as "micro-TMR" procedures, redirecting individual peripheral nerves to control specific contracting muscles. These individual groups of contracting muscles can thereby produce their own unique EMG patterns.

Most of these surgical techniques address the forward arm of the control loop, specifically the motor contribution. Yet, evidence suggests that sensory nerve fibres outnumber motor by a ratio of 9:1 in the human upper limb [57]. To truly perfect prosthetic control, the loop must be closed by providing prostheses with sensation [64].

Providing Sensation

The role sensation provides in hand movements cannot be underestimated. Sensation enables the light touch necessary to hold a fragile object delicately, or the positioning of finger joints in preparation for catching a thrown ball through proprioception. Emulating the natural sense of touch through engineering has proven challenging, so much that clinically available prostheses lack this most natural of functions. Beyond the necessary functional aspects that sensation provides, it also allows the users to become more connected with their prostheses, increasing it from a simple tool to an essential part of the user's body [65].

Reconstructive surgery works on the basic principal of replacing like with like where possible. So before attempting to engineer solutions to the sensation problem, it is worth considering what are the natural inputs of interest. Current neuroanatomical understanding broadly groups the ascending sensory pathways of the upper limb into three distinct pathways, respectively, responsible for fine (discriminative) touch, nociceptive inputs (pain, temperature) and crude (non-discriminative) touch, and proprioceptive information. Of these pathways, crude touch has been the most explored through laboratory studies to date.

Vibrotactile or electrotactile stimulators have been used to activate remnant crude touch pathways at the more proximal levels of the arm [66–68]. While relatively simple to implement, these systems are limited as pressure

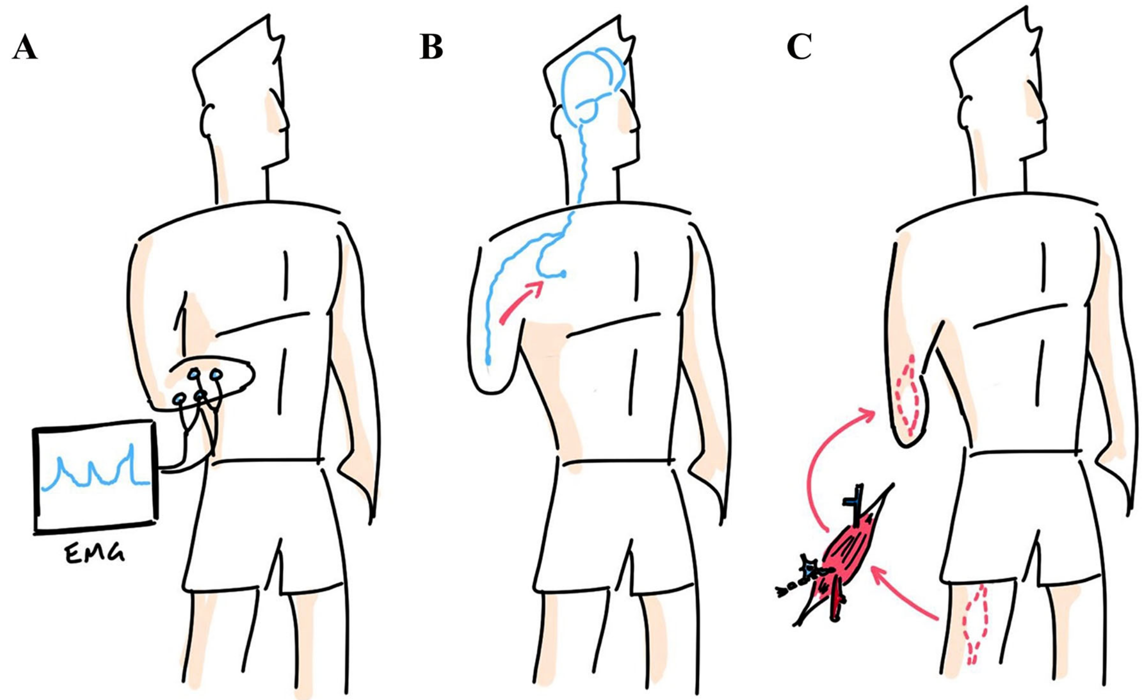

Fig. 3 Different levels of amputation determine the best engineering and/or surgical method to address the deficit. **a** In transradial amputees, the nerves to the remaining forearm muscles may still be innervating their desired targets, and EMG processing alone may be sufficient for adequate control. **b** In high-level (transhumeral/glenohumeral) amputees, TMR provides the ability to gain multifunctional and simultaneous control of prostheses. **c** Finally, in patients with complex injuries to a biological intact but insensate hand, such as from lower root brachial plexus injuries or critical soft tissue deficits, bionic reconstruction, which involves elective amputation and transfer of functioning muscle for prosthetic control, can restore useable hand function

changes at sensors located on the prosthetic hand are transmitted to non-discriminatory touch areas of the stump. This is disadvantageous, as the fine discriminatory pathways from the densely innervated natural fingertips are not specifically stimulated [69]. The neural topography of the stump can be altered using targeted sensory reinnervation, a variation of TMR [70–72], but the mechanoreceptors of the stump or chest region are different to the glabrous skin of fingers.

To overcome the loss of discriminative touch, attempts have been made to stimulate peripheral nerves directly. Intra-fascicular longitudinal flexible multielectrodes (tf-LIFE4) have been demonstrated to not only record motor impulses from peripheral nerves, but also to stimulate hand and finger sensation, albeit with decreasing efficacy over 10 days of implantation [73]. Expanding on these findings, stimulating electrodes have been implanted into peripheral nerves of amputees and their responses observed in response to touching mechanical stimuli. Using transversal intra-fascicular multichannel electrodes (TIMEs) implanted into the ulnar and median nerves over the course of 4 weeks, an amputee was able to accurately adjust the grip force of a prosthesis in a laboratory setting [74].

Progressing away from the laboratory environment, a case study of two transradial amputees demonstrated that cuff electrodes around peripheral nerves could provide a stable and natural touch sensation in their hands for more than 1 year [75]. Furthermore, a portable system including percutaneous flat interface nerve electrodes (FINEs) and/or spiral nerve cuff electrodes could stimulate sensation in a home environment [76]. The amputees had the electrodes in situ for approximately 40 months before participating in the trial and used the sensory capabilities of the home system for seven and 13 days, respectively. The simulated sensation of pressure of the prosthetic fingertips and degree of prosthetic opening were transmitted to the amputees by stimulation pulse trains of the respective nerves via the implanted electrodes. By providing sensation, the study found that the amputees used their prosthesis more frequently, in a more functional manner, with increased embodiment.

So far, these encouraging developments at tackling sensation have primarily focused on addressing the lack of touch. Proprioception is a more difficult sense to replace as naturally uses internal receptors, whether those are receptors that correspond to joint position or within muscle that transmit the degree of muscle stretch during movement. Still, there have been some interesting attempts in addressing this issue by combining intent, sense of kinaesthesia induced through external muscle vibration, and vision [77, 78]. Furthermore, there have been attempts to provide more natural spectrum of sensation by eliciting innocuous and noxious tactile perceptions in the phantom hand [79].

Current procedures for surgical amputation, typically performed in an acute setting, do not take into consideration the potential of residual nerves for future prosthetic control. As such, natural relations between agonist and antagonist muscle are sacrificed, along with useful nervous tissue. In an innovative animal model, paired free functioning muscle grafts were formed to create an agonist–antagonist myoneural interface (AMI) to overcome this problem [80]. Not only does the AMI model make use of the forward motor signals from agonist contraction to potentially control a prosthesis, but also gains feedback by creating the sensation of muscle stretch in the paired antagonist muscle.

These preceding systems have demonstrated that sensation can be stimulated using temporary percutaneous approaches, but as the technology matures a more permanent conduit may become useful. Osseointegration has previously been shown to provide a stable fixation point for prosthetic attachment [81], but additionally by utilising a hollow central channel in the implant allows for passage of electrodes for prosthetic control [82]. An intuitive control system, known as the osseointegrated human–machine gateway with perceived sensory feedback, is possible due to a bidirectional neuromuscular interface [81]. Using this system, closed loop prosthetic control by an amputee without the use of sight can be achieved, enabling grasping of delicate objects, such as eggs, without crushing (Fig. 4) [82]. While concerns remain over the risk of soft tissue and bone infections associated with percutaneous osseointegrated implants [83], novel totally implanted devices which provide more functional prosthetic movements [84] may eventually combine with emerging wireless technologies to overcome these drawbacks [85].

Individually these advances not only provide avenues to return sensation to prosthetic users, but as the prostheses become more part of the amputee will hopefully reduce device abandonment, leading to increased quality of life.

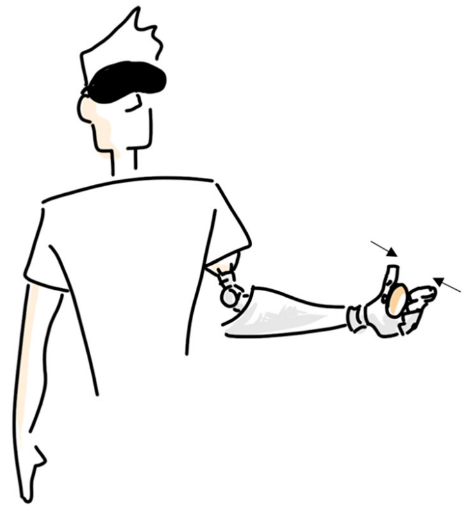

Fig. 4 Research into closing the prosthetic interface feedback loop has led to the development of an Osseointegrated Human–Machine Gateway. Bidirectional communication of direct neural information between an implanted neural interface and sensors in a prosthetic hand enables a user to blindly grasp fragile objects, such as an egg, without crushing

Advances in Rehabilitation

As increasing innovations are made by both engineering and surgical methods to improve upper limb prosthetic control, the rehabilitation methods are also continually evolving. For patients undergoing nerve transfers with the aim of providing useable myoelectric sites for surface EMG control, a structured rehabilitation programme is beneficial for optimal outcomes [86]. In the immediate period after nerve transfer, no voluntary muscle contractions are expected while nerves regenerate. During this healing period, therapy is directed towards cortical training of upper extremity motor regions using imagery and mirror therapy. Through gradual training, motor activity in the desired muscles develops. At first, this motor activity is imperceptible to the naked eye but is quantifiable using surface EMG recordings. EMG biofeedback is therefore used to direct the patients to generate activation patterns that correspond to the original nerve's function and intended movements. As the voluntary control of these patterns strengthens, visible contractions of muscles become apparent. Training now switches to reducing co-contraction of the original muscles that the donor nerves supplied while performing the intended movement. In addition to visible muscular contractions, both the therapist and patient benefit from visual feedback of EMG signals so they can optimise control. Once optimised, patients can then begin to use a prosthesis to conduct activities of daily living. Such a structured rehabilitation programme is not only beneficial in training the patients, but also during training of pattern recognition control systems [87].

Computer-based myoelectric training has been established for in-person occupational therapy visits, through programmes from Ottobock and TouchBionics, marketed as MyoBoy and Virtu-Limb™, respectively [88]. Open-source video games have been interfaced into virtual training systems for an entertaining method of exercising muscle coordination and improved myoelectric control using surface electrodes on top of the participants flexor and extensor muscles (Fig. 5) [89].

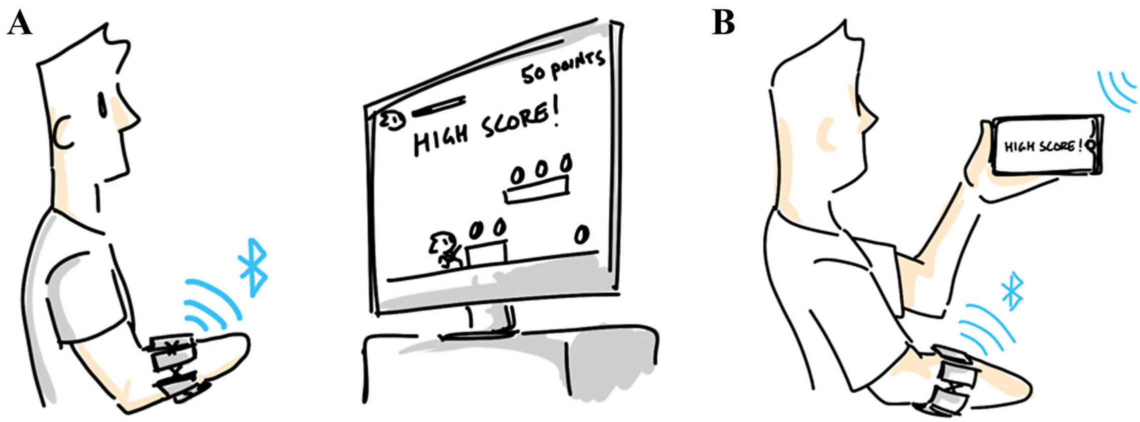

Fig. 5 **a** Video games, acting as virtual training systems, increase patient motivation to improve their muscle coordination and subsequently better myoelectric control. **b** Building on the development of PC-based rehabilitation games, the mobilisation of game-based rehabilitation through a patient mobile app. The mobile video games create myoelectric training opportunities outside of a clinical environment that can overcome logistic, monetary and geographic barriers to patient care [89]

Patient feedback has shown that the current commercial methods relying on simple EMG representations and wired interfaces are not as encouraging as game-based training systems [90]. Initial studies on mobile game-based training have shown the potential for increased training motivation through apps available on all major operating systems [88]. Games such as Volcanic Crush incorporate basic dual-site muscle activation, while Dino Spirit and Dino Feast build on Volcanic Crush and involve more complex sequential and then proportional movement control [88]. The next steps of game-based control rehabilitation and myoelectric training research should be aimed at the developments of mobile applications for long term at home use and the operation of advanced control methods, pattern recognition and regression techniques [89]. However, in order to achieve maximal training effect, a task-oriented myo-game should aim not only to motivate but also to enhance ADL-relevant features [91].

Conclusion

Gradually the combined research efforts of many groups are progressing towards the goal of returning hand function to upper limb amputees. During the past 5 years, regression-based algorithms have improved, and shown their potential to deliver robust multifunctional prostheses. However, these systems still require further refinement to catch up with pattern recognition systems which are emerging into clinics. Novel applications of materials are aiming to reduce the weight and cost of the devices while improving comfort and uptake of devices. Encouragingly, projects that are investigating provision of sensation to prosthetic hands are moving out of the lab environment and into home testing systems. There has been a change of focus where virtual reality environments and functional tasks in clinical tests are considered the most informative and preferred methods to validate novel control systems. Together with evolving surgical and rehabilitation techniques, the collective field is addressing patients' concerns [92] and providing solutions to upper limb loss.

Compliance with Ethical Guidelines

Conflict of interest Aidan D. Roche, Ben Lakey, Irene Mendez, Ivan Vujaklija, Dario Farina, and Oskar C Aszmann declare that they have no conflict of interest.

Human and Animal Rights This article does not contain any studies with human or animal subjects performed by any of the authors.

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