CHAPTER

UPPER LIMB ACTIVE PROSTHETICS: AN OVERVIEW

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19.1 INTRODUCTION/MOTIVATION

The world around us is by and large shaped to be operated by *hands* and *arms:* our homes, our workplaces, the means of everyday transportation, etc. For this reason, the loss of an upper limb is a tragedy, leading to a severe impairment in daily-living operational functionality as well as to psychological damage. Given the current state of the art in upper limb prosthetics in general (not just in active prosthetics), such a loss is irreversible. The impact of upper limb loss in our modern, ever-safer societies is less dramatic than that of other severely disabling conditions, for example, diabetes, stroke, and neurodegenerative conditions, or even if compared to *lower* limb loss—in 2010 about 1900 traumatic upper limb amputations per year in Europe were reported, maintaining an estimated total population of 94,000 upper limb amputees [1]. Still, if considered on a case-by-case basis, the loss of an upper limb has devastating consequences: the amputated person cannot operate any longer most of her usual daily appliances, leading to a dramatic lowering in the quality of life; living without a hand or the arm irreparably changes the looks and affective interaction of the amputated person, leading to social rejection, self-pity, and usually severe psychological consequences [2]. The fact that an amputation is definitive has led to the classification of prosthetics, as a subdiscipline of robotics, in *assistive robotics* rather than in rehabilitation robotics: an amputation is definitive and the amputated person needs an assistive device rather than a rehabilitative one, which should become the amputee's companion for life.

To partially recover the lost functions, man has for a long time devised a range of devices to be worn in place of the lost limbs and aiming at restoring the impairment to the best extent possible; but, especially in the case of the upper limb, the level of functional restoration has in general been poor, and we can safely say that it still is. Even neglecting other aspects of the problem, at most three degrees of activation (motor- or cable-driven joints)[1] can be simultaneously controlled, and in the stan-

[1]Whereas in most relevant literature one refers in this case to the "degrees of freedom" of a device, we prefer to use the term "degree of activation" or even "motor," since the two concepts do not match and usually a user's control is applied to movement/force/torque, that is on motors (usually in a coordinated way), not on degrees of freedom.

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dard case, not in a “natural” fashion [3]—the patient must learn to enforce a sometimes complicated sequence of muscle impulses to switch the control among the motors. Also for this reason, many amputees have preferred in the past, and still do prefer, to wear cosmetic prostheses, that is, passive arms/hands with the only capabilities to partially restore the patient’s looks and, possibly, to hold an object while the remaining limb operates on it; or even, *to wear nothing at all during daily life.* Rejection rates of upper limb active prostheses are high [4]: what can research and technology in this field *concretely* offer them, that cannot be done using an old-fashioned device or even a cosmetic one?

Only in the past 30 years have some branches of applied science and engineering really come together to try to advance the state of the art in active upper limb prosthetics [5]. But, as we will shortly see, today this problem remains no easy business, mainly, in our opinion, for one general reason: *research in upper limb prosthetics is holistic*, that is, it must be solved at all levels (e.g., dexterity, functionality, control, biocompatibility, man–machine symbiosis) at the same time, and solving only one subproblem will not usually lead to an established, acceptable, widely spread global solution. Decisive steps forward in upper limb prosthetics can be achieved only by involving the mechatronic engineer, the control theorist, the machine learning expert, the physiatrist, the certified orthotist/prosthetist and so on, all at the same time, or at least during the same process, their activity tightly integrated, and tailored for each single patient. Moreover, upper limb prosthetic solutions must be tested on the end-users, on-line, from the start; this requires that research laboratories cooperate with rehabilitation companies, facilities, hospitals, and so on, and involves knowledge of the psychological aspects of human–machine interaction, coadaptation and embodiment, the design of user interfaces, and functional assessment. It is a paradigmatically interdisciplinary problem, a feature that contemporary research facilities are usually in trouble implementing [2].

Before delving into the state of the art of active prostheses, two remarks must be clearly put out. First, one should draw a clear line between *academic* and *commercial* upper limb prosthetic hardware. There is a plethora of academic prototypes that have been, or are being, developed in university laboratories; we will not consider them in detail here, mainly because of the limited space, but all in all, note that the vast majority of such prototypes *do not* turn into commercial applications at the end of their life-cycle as research devices, and actually are never used for more than a few experiments. (There are remarkable exceptions to this; for example, the *Azzurra* hand, a commercial product stemming from the *Cyberhand* project [6] which, though not being certified as a prosthesis, is widely used as an academic prototype.) Without disregarding the related experiments, we believe that upper limb prosthetics is one of the highest forms of applied research: those solutions which do not find their way by and large were probably not suited to really be prosthetic hardware, or are not yet ready to be, or do not match the current state of the art, or more simply have willingly not been turned into certified devices.

Second, in this chapter we will focus on *active* upper limb prostheses and first give a bird’s eye view of early research, then we will try to paint a coarse picture of the state of the art in this field; but we will *not* refer to cosmetic and body-powered prostheses. This does not mean that the issue should be in general neglected: body-powered upper limb prostheses constitute an active field of research (see, e.g., Ref. [7]), and it has even been advocated that they are nowadays the most convenient solution [8]—an opinion we largely share. As opposed to a *self-powered* or *active* upper limb prosthesis, a *body-powered* one is generally operated via a cable whose tension is controlled by flexing/extending one’s shoulders; although this way only one degree of activation can be controlled, for example, opening and closing a terminal device suited for gripping objects, body-powered prostheses are reliable, since they do not depend on any (semi-)autonomous artificial system whatsoever, and provide force feedback to the subject thanks to the tension exerted, and corresponding resistance felt, at the shoulder girdle. In many respects they are still superior to active ones, not least because they cost a fraction of the price, which constitutes a further challenge for the researchers. The outcomes of the ARM competition within the *Cybathlon* challenge in 2016 are there to remind the assistive robotics community that the road ahead is still long: in both subsections the prosthetic arms "race" was won by athletes wearing body-powered prostheses [8,9] *with one degree of activation only*, a sad but instructive tuition for all of us.

19.2 THE PAST

While body-powered upper limb prostheses have been in use for centuries (if not, undocumented, since mankind has been able to use tools), the history of such devices begins soon after the Second World War [3], when small, light, and powerful motors were becoming available. At the same time, "myoelectric" control, that is, control enforced via the activation of muscle remnants, was conceived, thanks to surface electromyography (sEMG) [10–12]. This technique was already in use as a diagnostic tool to detect abnormalities in the activation of muscles, possibly leading to early discovery of neurodegenerative conditions. Indeed, the contraction of muscles generates an oscillating electrical field, whose magnitude hovers around 10–100 mV, which can be detected by silver-chloride electrodes (sensors). A significant alteration of its characteristics might denote abnormalities in the neural signals; on the other hand, the contraction of *healthy* muscles generates specific sEMG signal patterns, whose low-pass rectified version relates monotonically to the torque the muscle applies to a joint. In short, the envelope of sEMG can be used *to detect the intention to move* when applied to voluntary muscles.

After an amputation, the muscle stumps are usually surgically connected to the bone stump and, after the wound has healed, a good deal of remaining muscular activity can clearly be noticed in the remnant of the upper limb—this is evident even by palpation. Voluntary contractions of the imaginary limb[2] result therefore in quite specific isometric contractions in the stump, which sEMG is still able to detect [10,12]. The initial idea was a simple one: to identify at least two *loci* of maximum, independent muscular activity on the stump surface of a patient, and to accordingly use two sEMG sensors to detect such activity. Typically, for instance, trans-radial amputees can usually independently, voluntarily contract the remains of the *m. flexor digitorum superficialis* and *m. extensor digitorum superficialis* by trying to flex/extend the imaginary wrist. The two resulting sEMG signals are then used to operate the motor of a one-degree-of-activation hand prosthesis—usually opening and closing a gripper [13].

Thanks to an extremely well engineered, highly integrated sensor/socket/gripper solution, developed, tested, and improved to perfection over decades, prosthetic companies such as, for example,

[2]We hereby use the term *imaginary limb* rather than *phantom limb* since the phantom limb is usually cramped and, in general, cannot be activated by the amputees. The imaginary limb is informally defined as the missing limb "as it would move were it still present."

Ottobock and *Liberating Technologies* have been able to deliver a modular, complete solution to the clinics, de facto setting the commercial standard of active upper limb prostheses. Two sEMG sensors are housed in a semirigid plastic/carbon fiber socket, exactly at the loci of maximal remaining activity the physiatrist has identified, and the magnitude of the two signals is directly mapped onto the opening/closing velocity of a gripper and/or a wrist or elbow motorized joint. Velocity roughly maps to force at the end-effector when in contact with an object, which actually enforces smooth force/torque control of the prosthesis. Moreover, it is reported that amputees fitted with such a prosthetic device can still get force and motion feedback by listening to the noise produced by the motor as it closes around the object to be gripped. Therefore this solution provides both *proportional* force/velocity control and a simple form of physiological feedback; given that the remnant loci of activity have been carefully targeted, it also offers a quite high reliability [4,14]. On the other hand, its commercial price, as well as the time and price of servicing, constitute a severe disadvantage with respect to a body-powered prosthesis, which can usually be self-serviced and costs much less. The debate between two-sensor sEMG-based myoelectric control and body-powered devices is ongoing.

On the other hand, control over more than one motor, in turn controlling up to three degrees of freedom, has been enforced using the same hardware but defining some sort of sEMG “language” of co-contraction impulses, through which the patient can switch the proportional control among the motors [2,3]. Typical cases are control over hand opening/closing *and* wrist rotation in the case of trans-radial amputations, and over elbow flexion (no wrist control in this case) for trans-humeral patients. The user must briefly cocontract the two muscle remnants chosen, that is, push *both* sEMG sensors at the same time past a preset threshold, to obtain proportional control over one of the motors; each motor can usually be then controlled in a round-robin fashion. Smart as this control schema looks like, and notwithstanding its widespread usage in clinics, it clearly poses a relevant cognitive burden on the user, is more complicated than what a “natural” form of control would be, and can lead to unacceptable delays in emergency situations [15–17]. Such forms of control arose in the 1950s (e.g., a very early example is discussed in Reference [18]) and it is reported that the idea could even date back to not long after the Second World War (see Ref. [19] and references therein). In Philipson et al. [20] for instance, several examples of well-crafted two-sensor approaches can be found, and even a partition of a two-dimensional input space which somehow resembles a linear classifier.

More or less at this time the usage of more than two sensors and more sophisticated techniques to understand the user’s desire to move/act in a certain way *(intent detection)* was devised. In Ref. [21] it is claimed that the major hurdles to radical improvements in the design of prosthetic arms were an insufficient quality of sEMG signal processing (i.e., intent detection) and lack of light, fast, strong prosthetic hardware; it is approximately since the year 2000, however, that the academic interest in upper limb prosthetics has exploded [5]. This coincides with parallel progress in all areas of research concerning upper limb prosthetics: the miniaturization of sEMG sensors and the introduction of new kinds of sensors; ever-better motors requiring less and less power, to be embedded in an arm/hand system; ever-growing computational capabilities for signal processing and pattern matching, to be embedded on a prosthetic device; last but not least, an increasing awareness of the problems caused by the physical interface to the patient (the so-called *socket*).

19.3 THE PRESENT

19.3.1 DESIGN OF PROSTHETIC DEVICES

In the domain of hardware, the de facto standard active hand prosthesis is probably the *SensorHand Speed* by Ottobock [22], an extremely well engineered one-motor velocity-controlled gripper, usually activated via two sEMG sensors the way we have described above. The whole system has proved to be reliable and affordable and it can be furthermore coupled with a wrist "rotator," to be controlled using the switching procedure. This way, in total two independent degrees of freedom are offered to trans-radial amputees.

In an effort to augment the dexterity of a prosthetic hand, that is, informally defined, the number of motors it sports and therefore the number of movements it can enforce, researchers have tried to keep the control as simple as possible, actually exactly as it was before, but also to endow the device with a greater ability. A very interesting trend in this sense is that of exploiting underactuation and environmental constraints to build a prosthetic hand which, still using one motor only, can adapt to the surfaces of the environment, especially conforming to the shape of an object to be grasped. The *SoftHand* [9,23,24] and the *Hannes Hand*[3] are the latest developments in this subfield. Both hands work via one actuator only and, it is claimed, can enforce up to 90% of the functionalities lost by the hand amputee. Moreover, at least the SoftHand works according to the principle of muscle synergies [25,26].

As far as the other way is concerned, namely to build a device with more motors, therefore requiring a finer, more complex control (see Section 19.3.2 for more on this issue), at least two breakthroughs have happened with respect to the typical one-degree-of-freedom devices since 2008. The first is the appearance on the clinical market of multifingered prosthetic hands such as, for example, Ottobock's *Michelangelo*, Touch Bionics's *i-LIMB Revolution*, and RSL Steeper's *BeBionic*, with up to six independent motors, usually one for flexion of each finger and possibly one additional one for rotation of the thumb, or two different grasp configurations actuated using two motors and a gear change mechanism. From an exquisitely practical point of view, right now such devices lack proper controllability by the patient and their usefulness with respect to one-motor grippers or even body-powered prostheses is under question, especially given the associated buying and servicing costs. Nevertheless, they clearly show that more dexterity *can* be achieved even in the realm of prosthetic hardware, and to a commercial strength indeed.

The second breakthrough in prosthetic hardware design is represented by the main outcomes of the Revolutionizing Prosthetics program by DARPA (see, e.g., Ref. [27]), namely the *Modular Prosthetic Limb* (MPL) and its commercial counterpart, the *Luke Arm* [28]. The Luke Arm has been designed to be adaptable to most upper limb amputations (trans-radial, trans-humeral, at the shoulder level), and has one motor for each main degree of motion of the human arm—actually, 10 motors in the most complex configuration: two motors for the shoulder, two for the humeral rotation and elbow flexion, two at the wrist, and four in the hand; the hand in particular is gifted with a flexible and rota-

[3]The Hannes Hand has appeared, at the time of writing, only in the news—see, for instance, https://www.cnet.com/news/robotic-prosthetic-hand-hannes-lighter-cheaper-grabbier, accessed May 2019.

tional thumb, as well as with the flexion of the index and other (combined) fingers. The weight of the full-arm configuration is less than 5 kg. As opposed to this, the MPL has 17 motors to control 26 degrees of freedom, and is equipped with a high number of sensors (torque, position, contact, current, accelerometers). While the MPL is still an academic testbed and is not available for clinical use, its clinical testing is underway [29]; the Luke Arm has recently been certified as a medical device, and while its pricing and conditions of use are, at the time of writing, still unknown, the device can be bought from the manufacturer's website.

According to a recent survey we already cited [3] however, active prosthetic devices are not yet widespread around the world, and definitely not routinely fitted in clinics. Active prosthetic hands/wrists are endowed with two to four degrees of activation (actually six in the hand only for the *i-LIMB*), whereas some degrees of freedom are passively operated by mechanical design, that is, they must be activated by the user using a counteracting surface or the intact limb. The weight of such devices ranges in the few hundreds of grams (570 in the worse case). Active prosthetic elbows can weigh up to a kilogram (see again Ref. [3]).

19.3.2 CONTROL

Complex devices call for dexterous control, all the more reason for prosthetic control. Although, as already mentioned, the clinical standard still uses two sEMG sensors to control one or two motors, giant (academic) steps have been made in the past 20 years as far as "natural" control is concerned. The main trend in active prosthetics is to employ some form of machine learning, specifically called *pattern recognition* in the medical community, to directly interpret the user's intent to enforce a specific movement [30,31]. The issue that we have grouped here under the umbrella term *control* really consists of several different strands and subproblems: designing the ideal socket/implantation to connect the patient to a set of sensors; defining the number and kind of sensors and the required electronics; designing a suitable machine learning method to interpret the signals as reliably as possible. Each of these subproblems has proved to be extremely difficult *in practice*, despite the initial claims of success.

In the first place, implantation technology is still in its infancy—osseointegration [32] allows, for instance, a prosthetic device to be directly implanted in the user's stump and exceptionally low rates of post-operation infection have been reported so far; this technique also allows for the direct implantation of sEMG sensors within the stump, improving the signal-to-noise ratio and lowering the muscular cross-talk [33], via minimally invasive surgery or, in the near future, injection [34]. Still, large-scale testing of these methods has yet to appear, to the best of our knowledge. As opposed to that, the traditional device connecting a patient to an upper limb prosthetic device, the *socket*, presents, too, a series of difficult tasks to be carried out [35]. First of all it must be totally bio-compatible; second, it must ensure a perfect housing for the sensors, allowing for good conditioning of their signals, maintaining the contact with the user's skin/body at all times notwithstanding movement (both *external* and *internal*, meaning relative movement of the body and the socket itself), physical effort, skin irritation, and sweat. No techniques for the automated design of a socket are in sight, although 3D laser scanning is nowadays almost a commercial reality; also, it is hard to say what the best arrangement for the sensors should be, given the *loci* of maximal residual activity on the user's body. We believe that in this specific case it is paramount to design the device around the patient; but this concept seems still to elude the scientific community, or at least, we are unaware of any attempt to integrate the design process into the research environment dealing with control.

Notice that noninvasive, nonsurgical techniques to gather signals from the subject's body are still preferred over invasive ones for obvious medical and psychological reasons; but until the mid-2000s this left very little hope of any sensible function restoration to victims of more severe amputations, such as shoulder-level and trans-humeral. With the introduction of targeted muscle reinnervation (TMR) however [36], things have radically changed: patients who have undergone successful TMR surgery can produce activation patterns corresponding to actions whose musculature has been completely removed, for example, for elbow flexion in trans-humerals. In this case, such an activation corresponds to the activation of a re-innervated set of motor units, which can be still recorded by surface techniques [3].

Given that a uniform, safe, and effective way of connecting sensors and prosthetic devices is still not universally agreed upon, it is also interesting to note, however, that a good deal of research has been spent in determining *what sensors to use.* This subtopic of upper limb prosthetics has indeed produced a plethora of fascinating ideas (see, e.g., Refs. [5,37,38]), but sEMG remains the clinical standard. To what degree it can be integrated into, replaced by, or aided by other forms of sensing muscular activation, is still unclear. The most active field of research, to mention just one, is probably that of pressure sensing, either in its low-resolution (force myography) or high-resolution (tactile myography) variant [39–41]. The technique is promising, probably robust to muscular fatigue and sweat and it enjoys higher stability across time, but its practical applications are still lacking. Other techniques (ultrasound, mechanomyography, near-infrared spectroscopy, electrical impedance tomography, and so on) are still at the level of laboratory testing.

Last but not least, what is probably the most academically fruitful research field: the application of machine learning methods to biological sensors aimed at controlling an upper limb prosthetic devices. The number of scientific articles published in this field is high [5], while the practical results are definitely still not satisfactory. This is mainly due to the inherently probabilistic nature of a control system based upon machine learning. In Ref. [8] it is claimed that, in order to achieve a sensible level of reliability, any form of upper limb control system should reach an accuracy *in excess of six-sigma* in classification *in a practical setting* (whereas no such estimation is given for regression), which is still very far from the state of the art; any comparison of machine learning methods we are aware of is either performed in highly controlled conditions (i.e., in a laboratory) or reports accuracy values of up to 95%. Literally all possible machine learning methods, signals and features, linearity/nonlinearity of the models and training methods have been tried.

The most interesting paradigm shift is probably the introduction of the concept of simultaneous and proportional control, that is, the ability for the subject to modulate the activation of each single motor of the prosthetic device, at the same time and independently, or at least in a physiologically plausibly coordinated fashion [42]. It is a silent assumption that only by having a number of machine learning methods running in parallel this kind of control can be achieved; namely, using each machine to control a motor or a synergistic activation, and having built all models in such a way that muscle activation corresponding to a specific *intended* action will cause the prosthetic device to enact exactly that action—hence, the term *natural* control [15]. Simultaneous and proportional control is advocated nowadays as the main avenue to be pursued [3,5,17,43].

And still, notwithstanding this remarkable scientific production, there is only one company in the world, at the time of writing, selling a commercial solution which uses pattern matching, namely, Coapt LLC with its flagship product, the *Complete Control* system [44], which employs a simple but effective machine learning classification method and a fast data-gathering/calibration procedure based upon on–off goal-directed physiological stimuli. Complete Control uses eight sEMG sensors and can control opening/closing of the hand, flexion of the elbow, and one motor of the wrist.

19.3.3 AMPUTATIONS AND PATIENTS

Academic research in upper limb active prostheses is, in our opinion, still poorly patient-centered and very system-centered—no wonder, given that it is mostly performed in engineering laboratories. This is very likely one of the most important factors causing, in the very end, dissatisfaction and abandonment of prosthetic devices, and needs to be countered by putting the patient at the center—that means at least that a standardized procedure to treat upper limb amputees immediately after the trauma, or soon after the wound has healed and the user is awaiting to receive a prosthetic device, should be defined and accepted by all research facilities working in the field. Also, we miss a standardized functional assessment protocol *including the machine learning system* in the evaluation of the learning progress [45]. The closest approximation to that is the ACMC [46], explicitly conceived to test the functional recovery of upper limb amputees using a myoelectric prosthesis, but not taking into account the changes in the control system itself. In fact, the signals produced by upper limb amputated persons while learning to use upper limb active prostheses *change over time* [47–49]—a standard learning process, much like what happens while learning to use, for example, a new motorbike. In Ref. [43] it has even been clearly demonstrated that quasi-random muscle activation patterns can be learned, retained, and recalled after weeks, if those patterns were associated to a well-defined task. At the same time, since modern myocontrol is adaptive (based upon machine learning), *reciprocal* adaptation is expected to appear and in fact has already been observed (see, e.g., Ref. [49]). This form of synchronous change in time (coadaptation) should be fostered and exploited. It is probably not coincidental, that the Complete Control system allows for "recalibration" whenever required by the subject, thus improving the reliability and stability of the system. Actually, the performance of such a system can degrade over time (and indeed it will) because of several factors, in the first place those which make the sEMG signal quite nonstationary (sweat, fatigue, and so on) but, also, due to intervening novel environmental conditions or body postural changes. Anything which changes the muscular pattern corresponding to a definite action, for example, flexing the elbow, with respect to those gathered during the initial calibration, calls for recalibration or, even better, gathering of new data. This idea is enforced using incremental learning [50,51], which leads to interaction between the user and the machine learning system.

19.4 THE FUTURE: A SHORT NOTE

At the time of writing (2019), the commercial diffusion of active upper limb prostheses either (1) having more than two motors (degrees of control/degrees of activation), and/or (2) being controlled through more than two sensors, and/or (3) being adaptively controlled using machine learning is still scarce. CoApt LLC's Complete Control is the only case of ML-based adaptive control which is finding a way into the clinical market.[4] Obviously the applied research performed in the past 30 years can and should do more, and, although some parts of it are ready to be deployed in clinics today, they still have not appeared.

Lastly, we propose an overview of what we deem the forthcoming steps in active upper limb research. Consider Table 19.1, which graphically depicted the state of the art in myocontrol alone, for active upper limb prosthetics in 2011. According to the authors of this remarkable survey, progress in myocontrol has happened/was happening mainly along three independent directions of research (subproblems), namely toward a "proportional activation profile," that is, allowing for continuous velocity or torque control; toward multimodal "preprocessing," that is, employing more diverse biological sensors and possibly environmental information, too; and lastly, toward simultaneous, multifunction (multiactivation) intent interpretation.

We take up from their work and hereby extend Table 19.1 to our personal view of active upper limb prosthetics overall—the result is visible in Table 19.2. We identify the progress that has happened in 7 years along the subproblems of Table 19.1, and we add four more, in order to complete the picture.

[4]At the time of going to print, Ottobock has just released a new commercial pattern recognition system, called *Myo Plus.* No statistics about it are yet available as far as we know.

Table 19.1 The Three Main Subproblems of Myocontrol, and Their Perspectives, According to Fougner et al. [15].

Intent Interpretation	Single Function (One Motor)	Sequential Dual Function	State Machine	Classification (Mutually Exclusive)	Simultaneous Multifunction
Preprocessing	Single EMG feature	Multiple EMG feature	Multimodal		
Activation profile	On–off	Ramp function	Multilevel	Proportional	
→ **Time/research progress/ commercial diffusion**					

Adapted from Figure 2 in A. Fougner, Ø. Stavdahl, P.J. Kyberd, Y.G. Losier and P.A. Parker, Control of upper-limb prostheses: terminology and proportional myoelectric control - a review, IEEE Trans. Neural Syst. Rehabil. Eng. 20 (2012) 663–677.

Table 19.2 Seven Subproblems in Upper Limb Prosthetics, and Related Challenges/Ideas/Perspectives to be Addressed in the Upcoming Years, for the Benefit of Active Upper Limb Prostheses Users.

	Current	**Short Term**	**Mid-Term**	**Long Term**
Socket technology	Different for each patient and in each country; no standard mechanization	3D scanning; assessment of loci of residual activity; CAD design of socket	Semimechanized procedure becomes standard in the clinics	Completely automatic socket design, tailored to each patient
Prosthetic hardware	Electric motors; few or no sensors; up to 10 DoFs	Impedance control; sensors + closed-loop (position/velocity) control	3D printing to industrial strength; low-cost upper limb prosthetics	Tendon-driven activation; semisoft materials; human-likeness (?)
Sensors	Two sEMG sensors w/sequential control; eight sEMG sensors w/pattern recognition (CoApt)	Validation of novel sensors (tactile, ultrasound, etc.); sensors embedded in bio-compatible silicon	Targeted array of multimodal sensors and built-in miniaturized electronics	Sensor array built contextually with the socket
Proportionality	Present in traditional two-sensors control but only for one DoF at a time	Proportional control over some motors	Proportional coordinated control over all motors	Usage of (novel) muscle synergies to yield physiologically plausible coordinated control
Simultaneous control	None	Simultaneous control over a subset of the motors of the device	Simultaneous control over all motors of the device	
Coadaptation	Scarce evidence; assessment of signal change in the subject	Precise, qualitative, and quantitative assessment of parallel change of subject and control system	Correlation of functional improvement and coadaptation	Structured, standardized quantitative assessment of coadaptation, performed semiautomatically
Functional assessment	ACMC [46] is the only protocol targeting myocontrol—no focus on the control system	Protocols including the characteristics of the myocontrol system	Assessment with both user and control system in the loop	

→ **Time/research progress/commercial diffusion**

Notice that the "Current" column only considers commercial solutions; academic prototypes should be more understood as grouped in the "Short term" column.

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