CHAPTER

DESIGN PRINCIPLES OF A LIGHT, WEARABLE UPPER LIMB INTERFACE FOR PROSTHETICS AND TELEOPERATION

20

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20.1 INTERFACES FOR WEARABLE ARTEFACTS

According to Peter Cariani, *all technology is prosthesis* (see the commentaries to Ref. [1], p. 267), in the sense that whatever artefact mankind has ever built, it has built it in order to *augment in some way its own performances*. Examples are plenty: the invention and application of the wheel, which enabled our fellows of the Stone Age to carry objects that were unthinkably heavy; the invention of the printing press and its diffusion on a large scale, which enabled us all to read the classics; widespread usage of the steam engine, which has increased 100-fold the speed of traveling and transportation; and so on and so forth. However, irrespective of what exactly was invented, each new artefact has called forth for a specific user interface (*human–machine interface*, HMI from now on) to be designed—from the handles of the humble wheelbarrow to the pinch-and-zoom glass screen of modern smartphones.

Being able to properly control a tool is as important as the tool itself, maybe even more so, and control is enforced through an HMI. Unsurprisingly then, this concept is extremely wide, diverse, and complex: everything we do in our daily life has to do with (a series of specific) HMIs. Today, we operate electromechanical appliances at all times at home, at work, during our free time, while driving, shopping, walking, preparing dinner, etc., and in each case we need to be supported by a *dexterous* and *intuitive* HMI: by *dexterous* we mean that the HMI must enable *full control* over the device; and *intuitive* means that it must be *easy to understand and operate*, quickly and safely allowing the user to take the aforementioned full control.

The ideal HMI requires little training to let the human functional augmentation enforced by the device be enjoyed by the user to its full extent. It is, to use again Peter Cariani's metaphor, a seamless, transparent, effective connection to a prosthesis—after a while, the user forgets about it and happily uses the device as if it were a part of his own body [2,3]—this phenomenon affects both nondisabled persons in their everyday living as well as patients with musculoskeletal degeneration, amputees, and their phantom limbs, their pain, and sensations, stroke survivors in their rehabilitation

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process; in Ref. [4], for instance, the effects of tactile (touch) feedback on the perception of their own limbs by amputees is discussed. The rubber hand effect is a similar phenomenon easily elicited in perfectly healthy subjects [5]. Think about driving one's own car: while driving, can we not say that to some extent *the body of the car becomes (a transparent extension of) our own bodies?* It is no surprise then, that a lot of research effort has gone into the HMIs devoted to human–robot interaction. A robot is a complex artefact which must sometimes operate in hostile, unstructured environments, and it must be controlled to the best extent possible through a symbiosis, a coupling between man and machine—sometimes even leading to embodiment of a robotic artifact, exactly defined as the feeling that a robot has become a part of the user's own body.

Following up the previous contributions in this book dealing with wearable hardware/wearable robots, in this chapter we talk about some HMIs which are specifically conceived and designed to control wearable robots, specifically for disabled persons such as upper limb amputees, and specifically enforcing coadaptation of man and machine using biological signals. Such HMIs pose to the researcher and the engineer a set of challenges on top of the standard ones—they must be lightweight, low power, robust to signal variability and to the diversity of human interaction with the environment; moreover, most of these interfaces are to be used by persons whose bodily functions are hindered when not almost totally absent, which, if possible, makes their design even harder.

We will first try to highlight the current problems associated with these HMIs, then discuss the pitfalls in which the scientific community is still getting entangled and does not yet clearly know how to overcome, and finally give a set of suggestions/guidelines/design principles on how to sensibly enforce a tight human–machine interaction using them.

20.2 CURRENT PROBLEMS

Let us for the moment restrain to upper limb prosthetics. Upper limb prostheses are possibly the quintessential wearable artefacts: not only *must* they be actually worn to be of any usefulness whatsoever, but they must be unobtrusive, biocompatible, and at the same time they must allow for delicate tasks such as those of daily living (extreme precision) as well as for heavy work in hard weather, in stress conditions, or for long times [6]. Wearing an upper limb prosthesis for 8–12 hours a day must in no way lead to, for example, skin irritation and eczema, body posture alteration, nerve compression, and musculoskeletal impairments related to fatigue. Physical discomfort and mid-term nerve strain or tilted gait are widely reported among the problems associated with active upper limb prostheses [7–9]. Rejection rates still appear to affect one third to 80% of all prosthetic users worldwide [9–11], to the extent that—some authors claim—body-powered arms and grippers are still better than mechatronic arms and hands [6,12]. The main critique is that there is as yet very little a mechatronic arm/hand system (myoprosthesis) can do, that cannot be done using a body-powered device (that is, a mechanical arm operated using a cable harnessed around the shoulders); actually, too little to justify the cost, weight, heat production, and long maintenance times required by these devices. The results of the Cybathlon ARM competition 2016 seem to point in this direction, too [6].

But let us for the sake of the argument assume that we could have at our disposal the ideal, modular, mechatronic arm/hand system: easily adapted to the degree of amputation (trans-radial/trans-humeral amputation, shoulder disarticulation), weighing like a human upper limb, having a similar payload and enough motors/motion capability/strength to restore, say, 95% of the functionalities lost after an upper limb amputation, both in daily-living activities and during hard work. How would we let a human subject properly control this device?

The answer generally provided by the scientific community (and there is no other one in sight, to the best of our knowledge) is that several different kinds of signals—actually, as many and as diverse as possible—should be used to detect the intended action/movement/application of force/muscle activation [13]. Such representative signals are to be gathered from the subject's body, possibly noninvasively or minimally invasively; then, as directly and naturally as possible, they must be "turned" into those prosthetic control commands required to enact the desired movement/action/activation. Simple as it sounds, this is a so-far by and large unsolved problem [14]. We identify three large areas in the design of an upper limb HMI where the state of the art at the time of writing is still insufficient, namely: the sensors and the signals they provide, their physical interface to the human body; and the control/intent detection system itself.

20.2.1 SENSORS AND BODILY SIGNALS

In mammals, torques and forces at the skeletal joints and, in the very end, movement, are produced via the (voluntary, graded, simultaneous, coordinated) activation of muscles; it is therefore quite an obvious choice, when aiming to detect the intention to move or act with one's arm and hand, to employ sensors able to estimate such activation, either directly connecting to the nerves responsible for motion and sensation in the arm [15] or by exploiting the muscles themselves as amplifiers of the neural signals [16]. We focus on the latter alternative, since the first is still in its infancy mainly due to the technological difficulty associated with a proper, informative, long-lasting and bio-compatible connection to nerves. Since the 1950s, the reference method to estimate muscle activity has been surface electromyography (sEMG) [17–19], used to control opening and closing of prosthetic one-degree-of-motion grippers such as, for example, the *SensorHand Speed* by Ottobock [20]. sEMG exploits the depolarization waves traveling along the muscle fibers during muscle activation to estimate the percentage of maximum voluntary contraction currently being enforced [21]; notwithstanding the low intensity of such electrical fields (in the order of magnitude of 10 mV), the cross-talk among adjacent fibers, the attenuation due to fat tissue, and the noise due, among other factors, to muscle fiber recruitment, it turns out that well-engineered sEMG sensors can effectively detect the activation of large surface muscles, or of their remnants after a traumatic event such as an amputation. In practice, in the case, for example, of trans-radial amputees, a physiatrist would spot at least two *loci* of residual *independent, stable, and repeatable* voluntary muscle activity on the patient's stump, and design a housing for such sensors inside a semirigid *socket*, such that the sensors remain in place as precisely as possible. The subject must then learn to activate such muscles (usually, the *m. flexor digitorum superficialis* and the *m. extensor digitorum superficialis*) to operate the opening and closing of the prosthetic gripper. More complex schemata using cocontraction to switch among motors can be used to also control, for example, a wrist rotator.

As early as 1969 though [22], in an attempt to control more than one motor or to enforce more than one movement (opening/closing), researchers have tried to apply *pattern recognition* to an array of more than two sensors. On one hand, this idea has produced the unwanted side-effect that much research has concentrated on improving the recognition method rather than on its practical application—the result is a *corpus* of scientific publications showing improvements of a few percent in offline analysis, with hardly any practical application [14]; whereas, it is now widely recognized (see, e.g., Refs. [23,24]) that offline classification performance of machine learning methods, as well as performance obtained in highly controlled laboratory conditions, does not generalize to online usefulness. On the other hand, using many sEMG sensors simultaneously has proved to be easy in principle but extremely hard in practice, mainly due to well-known problems associated with sEMG. Such problems would hardly matter when two sensors only are used, and on large superficial muscles, but turn into formidable hurdles in this more complex case: sEMG is extremely sensitive to sensor displacement and detachment from the skin; it can hardly gather the activity of deep muscles due to distance, cross-talk, and fat tissue, in which stumps are usually rich; and even muscular fatigue will significantly change it whenever it kicks in, which unfortunately is usually the case given the weight of prosthetic devices [21]. On top of this, the electronics required for a proper conditioning of many sEMG sensors, with a bandwidth of 15–500 Hz, can be problematic both in terms of computational power, electrical power consumption and—major problem!—weight and heat issues. (The recent advancement proposed in Ref. [25] looks extremely promising in this sense.) Attempts in this sense have appeared in the scientific literature (e.g., [26,27]) and actually, in the case of patients who have undergone targeted muscle reinnervation [28–31], this is still the only possible solution and its drawbacks must somehow be coped with.

The problems associated with sEMG are also being countered, and to some extent solved, although not in clinical practice so far, by employing more invasive forms of sensing—requiring minimal surgery to be implanted in the body. Osseointegration [32] is being tried for trans-radial and trans-humeral amputees as a radical form of man–machine integration: in this case a prosthesis is directly affixed on the stump using a titanium pin fixed in the bone stump. This technique solves all sEMG drawbacks due to displacement, cross-talk, and sweat: during the implantation of the pin, intramuscular (nonsurface!) EMG sensors can be fit within the remnants of the stump muscles; cabling occurs *through* the pin itself. The advantages are a higher signal-to-noise ratio than in the surface case and minimal cross-talk due to a careful insertion of the sensors. But even if osseointegration is not planned, bio-compatible miniature EMG sensors can be implanted in the user's muscle remnants and left inside for an indefinite amount of time; in this case, an electromagnetic induction coil, wrapped around the stump, both supplies power to the sensors and receives their signals [33,34].

On the other hand it has been advocated (e.g., in Refs. [10,13,14]) that novel kinds of sensors be devised, tested, and applied in practice. A plethora of new ways to gather muscle activation has flourished in the academic laboratories: listening to the sound produced by contracting muscles (mechanomyography) [35,36]; using ultrasound imaging or linear sensing to detect the displacement induced by the contraction in the deep structures of the body (sonomyography) [37–40]; using the injection of light or small electrical currents to do the same job (near-infrared spectroscopy, photopletysmography, electrical impedance tomography); using pressure sensors to detect the deformation induced at the surface of the stump by the contraction (force- or tactilemyography) [41–43]; and even using computer vision to detect such deformation by just looking at the stump (optical myography) [44]. Each novel technique promises a different way to overcome the limitations of sEMG but at the same time introduces new problems and pitfalls: pressure sensing, for instance, is by and large insensitive to sweat and fatigue, but is sensitive to artefacts induced by movement and bumping; ultrasound and similar tomography techniques are usually extremely sensitive to relative motion of sensors and stump, although they provide useful information on the activation and induced motion of deep body structures, usually inaccessible to their surface counterparts. Optical recognition is probably the most noninvasive technique but, like standard computer vision, it is affected by changes in illumination, position, orientation, and distance. (A thorough review of alternative muscle activation detection techniques can be found in Ref. [45]). To these limitations it must be added that each kind of sensor needs proper signal conditioning, in turn requiring dedicated electronics, which in turn, once again, means power consumption, weight, and heat.

On a slightly different note, inertial sensing and the use of data related to acceleration have gained quite a lot of attention lately [46] and are now being explored as one of the further ways to enhance intent detection: coupling these data through a smart integration/filtering schema, one can reasonably reconstruct the *kinematics* of (the remnants of) the upper limb (relative position, for instance, of the shoulder, upper arm, and lower arm), which is a potentially very useful source of information, since some tasks in daily living are typically performed while enacting a very specific arm/hand configuration. (The Modular Prosthetic Limb [47] in its commercial incarnation, the *Luke Arm*, can even be controlled using inertial sensors placed in the user's shoes [48]!) Properly estimating this configuration can constitute a substantial prior to the prediction of a desired set of actions, namely those involved in a specific task (academic attempts at using such priors appear in, e.g., Refs. [49,50]). For instance, while trying to open a jar by unscrewing the lid, the hands are placed one above the other, one of them holding the jar laterally/cylindrically, while the other one grabs the lid with a circular grasp. This information can be used, for example, to select a subset of the grasping actions available to the control system, thereby improving its recognition rate. A great advantage of these sensors is that they are nowadays cheap, efficient, and extremely light, even when coupled with a wireless transmitter; the popular *Myo* sEMG bracelet by Thalmic Labs (no longer in production) already contains an accelerometer and an inertial measurement unit (IMU).

On the other hand, their usage is limited by the unavoidable integration errors which accumulate through time and appear in the tracking as a drifting behavior. A smart recurrent recalibration schema and/or adaptation by the subject can mitigate this problem. Notice that the usage of an accelerometer and IMU data is already advocated in the 2011 survey [10]. Also, at the time of writing, commercial components which seem to be virtually drift-free have appeared on the market [51].

In general no silver bullet has been found yet: the limitations of sEMG are well known to the community, but no-one knows what novel sensors could replace it, or be proficiently coupled with it, to really get a better understanding of the intended muscle activations. Possibly, force and tactile sensing are the frontrunner (see, e.g., Refs. [42,43,52]).

20.2.2 THE PHYSICAL INTERFACE: PROPERLY HOUSING THE SENSORS

Any HMI of the kind we have described above must be wearable, almost by definition (some of the computation could be devoted to another wearable device, e.g., a smartphone). Additionally, in case the mechatronic device to be controlled is a prosthesis, it must be worn at all times during its usage. This places a non-negligible burden on the user, where *burden* is meant in its literal sense—weight added for the user's body to carry around. Permanently adding weight on a body can have many detrimental consequences—postural problems, nerve and muscle strain, skin edema and rash—for this reason, the design of the physical interface/attachment, the socket, of a prosthesis to the body is an extremely important part of the prosthetic design *tout court*, highly tailored on the user and specifically on the type of amputation (more generally, on the type of disability) [53]. On top of this, sockets for upper limb disabilities must enable the user to achieve the largest possible range of motion, in the ideal case equal to the range enjoyed by the lost limb—especially for shoulder disarticulations this can be highly problematic (see, e.g., Ref. [54] and references therein). Also, sockets must be easy to don and doff, and the performance of the prosthetic system should remain comparably good irrespective of donning and doffing.

In our case, the socket additionally houses the sensors. Traditional sEMG sensors, as well as essentially all sensors being tried in the academic environment, must remain as much as possible in the same spot of the body of the user irrespective of donning/doffing (avoid electrode displacement) and stay in contact with the skin—a detached sensor will yield a signal artefact and confuse the control system (sensor lift-off). Of course, embedded sensors add weight to the socket, as does their power supply and the cabling; and, as mentioned above, some sensors suffer from specific changes in the morphology of the body and from physiological issues. Unfortunately, the added weight calls in the end for more muscular effort, which has the precise effect of eliciting fatigue and changing the muscle configuration. Due to all these reasons, designing a good socket remains more of a highly skilled craft than a science [53,55], and can significantly increase the overall cost of the prosthetic fit.

20.2.3 SIGNAL PROCESSING, MACHINE LEARNING, ADAPTATION

As long as two sEMG sensors are used, a simple form of proportional control has been enforced in the past: the amplitude of the rectified signal is used to operate both ways one motor of the prosthesis. More motors can be controlled by enforcing a coded sequence of activation impulses, for instance co-contraction (simultaneous activation) of the flexor and extensor would signal the desire to switch from controlling the gripper to controlling the elbow [56]. On the other hand, machine learning methods, typically called *pattern recognition* in the medical/rehabilitation field, have been applied whenever more motors needed to be controlled, and/or whenever a relatively larger number of sensors and signals was available [14]. sEMG patterns have been classified in all possible ways, in the hope of detecting what the subject wants to do and accordingly control the prosthesis. Whereas in the beginning this approach seemed highly promising, it was soon discovered that it would rarely work in practice: although extremely high classification rates were obtained while analyzing offline sEMG data collected while one or more subjects were enforcing grasping patterns (usually in highly controlled laboratory conditions), this would not correspond to any practically applicable control system [23,24]. The only success story so far is represented by CoApt Engineering's *Complete Control* system [57], which employs up to eight sEMG sensors and an entry-level classification method to actuate three motors (wrist, elbow, and hand) [58]. In fact, to the best of our knowledge, the overwhelming majority of machine learning/pattern recognition systems tried out in the literature are *classifiers*, which ironically gives up on proportional control of force and velocity, which is enjoyed by the traditional two-sensors schema. For this reason, in the 2000s, the idea of using simultaneous and proportional control was introduced [59,60], leading to natural enforcement of the user's intent (intent detection).

All in all however, even if we are restricted to the machine learning method, that is without considering the quality of the signals and of the socket, it has been remarked that (1) the variety of situations to be encountered in the real world while operating a self-powered prosthesis in daily living is overwhelming with respect to the typical initial calibration [61]; at the same time, (2) the classification accuracy which *true* prosthetic usage requires is way higher than any value so far achieved in controlled conditions [6].

On top of this, any machine learning method designed for practical usage should be compact enough to be run on a microcontroller, or at least on a portable device such as a smartphone; also, calibration times cannot exceed a reasonable threshold, due to the expectation of the subject being able to seamlessly and quickly use the device at all times.

For these reasons, incremental and/or bounded approaches have lately been preferred [62,63]. Incremental approaches also have the advantage of engaging the user in an interactive loop, which potentially induces coadaptation leading to an ever-better symbiosis with the prosthetic device [1,64]. These remarks also justify the success obtained by the Complete Control system: the actions controlled by the system are enforced by independent groups of muscles (hand, wrist, elbow), resulting in highly separable and repeatable patterns, even given the small number of sensors. On top of that, the "recalibration" procedure allowed for by Complete Control allows to somehow counter the nonstationarity of sEMG. To some extent, this looks like the need for periodical recalibration of IMU and accelerometer sensors. As long as recalibration is fast and does not need to happen too often, it is fine and the system is practically usable. It seems that so far the simplest solution is the winning one, at least from a commercial point of view [65,66].

20.3 DESIGN GUIDELINES FOR A WEARABLE UPPER LIMB INTERFACE

Let us then try to imagine how the ideal HMI would look. Although we hereby focus on upper limb *prosthetics*, most of what we say here also applies to other applications for such an HMI: for instance, a robotic arm/hand system teleoperated by intact (i.e., nonamputated) human subjects [67], either in an assistive or industrial scenario; or an *app* on a consumer smartphone, through which to control one's own self-driving car, smart home, and appliances, an avatar in virtual or augmented reality, and so on. We claim that prosthetics are among the hardest applications for such an HMI, meaning that if it works in this case it will probably also work in many other cases. (See also the final remarks to this chapter.) Therefore at the time of writing and to the best of our knowledge, the most advanced complete, certified prosthetic arm is the Modular Prosthetic Limb (MPL), developed at the Johns Hopkins University [47], now in its initial clinical evaluation [68]. Upper limb amputations constitute a wide range of different disabilities, mainly depending on the level of amputation (trans-radial, trans-humeral, shoulder); the MPL was designed modularly, in order to be adapted to the type of amputation. What would the ideal HMI for the MPL look like?

20.3.1 CURRENT PITFALLS

At the beginning of this chapter we called for two main characteristics of the ideal HMI: dexterity and intuitiveness. Matching these two requirements with the overview of the state of the art presented in the previous section, we can identify the following pitfalls that currently hinder the way toward the ideal HMI:

- *Nonsystematic design of sockets.* Physically connecting the sensors, the electronics, and the prosthetic device to the subject's body is still a manual craft, largely varying in quality across countries and even rehabilitation facilities within the same country. Three-dimensional (3D) laser scanning, the use of professional CAD design, and 3D printing, could be useful tools toward mechanization/

standardization of the procedure to build sockets—including precise tailoring of the socket to the needs of the patient and to the device to be used.

- *Too little knowledge about sensing.* What kind of sensors are better suited to detect which kind of activity; what features to extract from each data stream; and how to combine the sensors, both in hardware and in software; these factors are still, in practice, unknown.
- *Too few sensors and/or insufficient targeting of the stump.* Irrespective of the kind of sensors and their combination, *more* sensors are very likely to be required to build a control system at the ideal level of dexterity of an HMI. To this aim, we should either enforce higher spatial resolution, that is, many smaller sensors uniformly placed on the user's body, and/or better targeting of the *loci* of activity the control system is interested in recognizing. (Targeted muscle reinnervation is a remarkable step in this direction.)
- *Weight, power consumption, biocompatibility, appearance.* The whole system must be worn for a long time without causing postural and/or skin problems; therefore it must be ergonomic and lightweight, produce as little heat as possible, consume as little power as possible, enforce biocompatibility and resilience to body shape changes and sweating, and last but not least it must look human in order to be socially acceptable. These aspects are frequently mentioned passim, neglected, or even omitted from the scientific research—the integration of all these requirements constitutes a *formidable interdisciplinary challenge*, whereas research teams often tend to concentrate on other aspects [6].
- *Nonnatural control.* Back to the remark we made at the very beginning of this chapter, *control is as important as the tool to be controlled.* Now, controlling the ideal upper limb prosthesis is a complicated task; therefore (1) *natural myocontrol* must be provided (simultaneous, proportional, incremental), and (2) the control system as a whole must work through an effective *graphical* user interface—much like what the Android or iOS operating systems are to smartphones. The functionalities offered by contemporary smartphones are extremely complicated in principle; nevertheless, such operating systems turn learning to use such devices into a simple, intuitive, exciting experience. So should be the "operating system"/GUI of a dexterous prosthetic device.
- Last but not least, *lack of coadaptation.* A prosthesis should in the end become an intimate object, a part of the user's body, which, given the current state-of-the-art, is impossible. The ideal HMI is so fast, precise, responsive, and intuitive that it provides the user with a strong feeling of immersion since the start; if the device responds quickly enough, the immersion can be so strong that the user will introject the device as well as the control system itself, embodying the system.

  This issue is strongly coupled with the

- *lack of sensory feedback*, which is a so-far much less explored field than that of intent detection (feedforward signal processing versus feedback signal interpretation leading to sensory substitution) [69]. The ideal HMI is actually a *bidirectional* HMI (bHMI).

20.3.2 IMPLEMENTATION AND TESTING

Implementing a bHMI which overcomes the above-mentioned problems implies several design requirements. We hereby divide these into two categories: *patient-specific* and *nonpatient-specific*.

Patient-specific requirements are those constraints imposed on the bHMI which arise from the user's needs and desires. Given the level of amputation, the condition of the stump, and the general psychophysical condition, and given the available prosthetic device, the design of the ideal bHMI goes through the following steps:

- Identifying the remaining muscle activity and matching it with the degrees of activation (motors) offered by the prosthesis; in the presence of TMR, the use of the sensorimotor reinnervation map is paramount;
- Choosing a set of sensors adequate to detect the remaining activity as best as possible, and to control all possible degrees of motion of the prosthesis;
- Choosing the optimal placement of the sensors and accordingly designing the socket—this step must by all means take into account the musculoskeletal condition of the user.

Nonpatient-specific requirements are, moreover:

- To embed the computation (that is, the required electronics) inside the socket/prosthesis complex; or at least, that the computing machinery be unobtrusively wearable, for example, on a smartphone or a tablet;
- To keep the system as light and low power as possible; a reasonable estimation is weighing less than 400 g including the battery and lasting at least 8 hours;
- To provide natural, simultaneous, and proportional control over all degrees of motion of the prosthesis;
- To provide an incremental machine learning system as the core control component, in turn providing on-demand model updates and corrections; and lastly,
- To provide an intuitive user interface to manage the interaction.

20.3.3 FINAL REMARK: NOT JUST PROSTHETICS

We believe that a bHMI such as the one outlined above also has a range of less dramatic, but not less interesting and useful, applications. Training an amputated person to use such a system entails inducing this person to produce "ever-better" signals, enforcing clearer patterns in the course of time. Given the lack of sensorimotor feedback caused by an amputation, or even worse, the presence of a strong phantom feeling which potentially contradicts the motor intention, this learning process is usually long and, in some cases, even painful. Therefore applying these guidelines to "simpler" applications should be possible with a reasonable effort; here are a few directions in which the strong requirements on upper limb prosthetics can be lifted, in each case leading to a new realm of possibilities for the ideal bHMI.

1. *Amputated persons could use the bHMI to control an avatar in virtual reality/augmented reality (VR/AR) instead of in real tasks*—they would literally *see their missing limb back in action*, with potentially astounding psychological effects. VR/AR has two advantages with respect to prosthetics: first, the unlimited range of possibilities for the experimenter to build worlds exactly targeted at a specific objective to be enforced by the system—serious games to reduce phantom-limb pain, a mechatronic simulation of the prosthesis the patient is waiting to receive, and so on. Second, the lack of haptic interaction with the virtual world: the weight added to the musculoskeletal system while grasping, carrying, and manipulating an object in "real reality" will significantly alter the user's muscle configuration, leading to instability in machine-learning-based control methods. In VR/AR this problem does not exist, leading to a simplified interaction with the virtual world.

(Note that the lack of haptics is deemed to be the main drawback of VR/AR, but here it can be exploited for a good reason.)

2. *Intact subjects could use the bHMI better than amputated/disabled persons* (although, see, e.g., Ref. [43] for a somewhat contradictory example). In the case of able-bodied people designing the physical attachment is simpler, and the healthy sensorimotor feedback helps to produce exactly the required signals. Therefore the bHMI could proficiently be used to have intact users teleoperate their avatars in VR/AR, or an arm/hand system in a remote location. Interfaces such as this could not enforce the same *precision* a standard HMI does—picture position control using sEMG versus magnetic or optical motion tracking of an arm, or even simply the usage of a joystick—still they can enforce a more natural control, leaving the hands of the subject free to operate (i.e., no sensors/markers on the fingers, nor a glove) and be light, a very desirable characteristic when operating, for example, in space.

As an example, Fig. 20.1 is our personal view of one such ideal bHMI, one which would work for both able-bodied and trans-radially amputated persons, both in VR/AR and in reality, both while using an upper-limb active prosthesis and a tele-operated arm/hand system. The interface consists of three submodules: an intent-detection/sensory feedback bracelet with embedded IMU placed on the forearm, and two more IMUs placed on the user's back and upper arm. Intent detection happens using, for example, sEMG, force, or tactile sensors embedded in the bracelet; sensory feedback is enforced via electro-cutaneous stimulation [69]; and thanks to the three IMUs the kinematics of the arm/hand can be reconstructed. A standard transmitter, for instance via Bluetooth, embedded in one of the submodules, makes the bHMI completely wireless, giving the user maximum freedom of movement. The total weight of such an interface is estimated in a few hundred grams including one or more batteries. All required computation can be run on a portable device such as, for example, a smartphone, or, most likely, even on a microcontroller embedded in one of the submodules.

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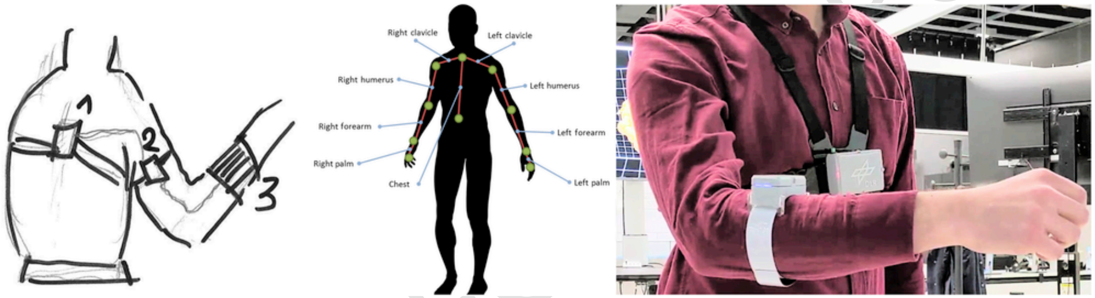

FIGURE 20.1

(Left) Sketch of a bidirectional HMI consisting of an intent-detection/sensory feedback bracelet with embedded IMU on the user's forearm or stump (3), two further IMUs on the user's back and upper arm (1, 2), a Bluetooth transmitter (1) and a battery (1). (Center) Abstract schema of a possible placement of parts of the the interface. (Right) A prototype of such an interface, currently in use at the author's laboratory.

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