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Review Chapter

INTRODUCTION TO UPPER LIMB PROSTHETICS

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SUMMARY

The progress in upper limb prostheses has been moderate for decades. Only recently have new commercial prosthetic developments become clinically available. This new generation of devices offers better functionality and new compliance components by improved mechatronic designs that utilize advances in materials, rechargeable batteries, and actuators. Compared with human limbs, however, the performance of these new prosthetic components is still very limited. Further progress is hampered by the limitations in the human–machine interfaces that control these devices. Their signal processing and control mechanisms, which are usually based on myoelectric activity, are still very similar to conventional systems. That is, control signals are still derived from a small number of myoelectric signals recorded from surface electrodes. Consequently, the information transfer rates are very limited, the control of various degrees of freedom is cumbersome and slow, and using surface electrodes causes a number of practical problems. Academic research has suggested various ways to overcome these problems and significantly improve the human–machine interface.

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The possible solutions include shared control approaches, advanced signal processing, selective nerve transfer, new noninvasive and invasive signal acquisition methods, and methods for providing somatosensory feedback. However, many of these new technologies still require considerably more research before they can become clinically available.

INTRODUCTION

Prostheses are artificial substitutes that replace missing or lost parts of the body. There are many different artificial replacements for body parts available now. For instance, heart valves, teeth, arteries, and joints can be replaced by artificial parts, which are then called prostheses. However, the artificial components that are most commonly regarded as prostheses are those that replace limbs. To better differentiate the various forms of prostheses, the terms **endoprostheses** and **exoprostheses** are used. Prostheses that replace parts inside of the body are called endoprostheses. In contrast, exoprostheses are applied outside of the body. Typical exoprostheses are artificial replacements for the upper or lower extremities. Artificial substitutes for fingers, hands, wrists, forearms, elbows, upper arms, or shoulders are also termed **upper limb prostheses**. Correspondingly, exoprostheses for the lower extremities are also called **lower limb prostheses**.

Neuroprostheses are another form of prostheses that have been gaining considerable attention over the last decades. Neuroprostheses are devices that are direct or indirect interfaces to the central or peripheral nervous system and can substitute lost or impaired motor or sensory functions. Examples are cochlear and retinal implants as well as invasive and noninvasive brain–machine interfaces (BMIs). Although conventional artificial limbs have not much in common with neuroprostheses, new developments of exoprosthetic devices that use neural human–machine interfaces have an increasing similarity to motor neuroprostheses.

As is often the case in science and engineering, the terms used for specific applications or technologies are coined by the field in which they have been developed. *Prosthesis* is a term traditionally used in the field of orthopedics. A very closely related term but used in the field of robotics is *robotic arm* or *robotic hand*. In general, a robotic arm is a robotic manipulator with functions similar to the human arm (and hand). Robotic components can be large and heavy, can work in hazardous and hostile environments, and can perform tasks such as welding or assembling of parts in industrial environments. However, wearable robotic arms or hands are worn by human operators and can supplement the function of a limb or replace a limb completely (Pons et al., 2008). If such a robotic limb substitutes the human limb, the terms robotic arm and robotic hand are synonymous with prosthetic arm and prosthetic hand, respectively. Wearable robots may also embrace and support an already existing limb to restore functionality in case of an impaired limb or to enhance functionality beyond the capability (e.g., strength) of a normal healthy limb. Such wearable robots are also called **exoskeletons**. Exoskeletons in turn share many similarities with orthoses, which are orthopedic medical devices that support, correct, or restrict the function of body parts.

Most patients require exoprostheses as the result of amputations. Patients suffering from dysmelia, which is a congenital disorder that can result in missing limbs or malformations of limbs, may require prostheses as well. Larger statistical surveys about the number of amputations are rare. Dillingham and co-workers identified 52 amputations per 100,000 persons in the United States for the year 1996. Five of these amputations were related to upper limb, 47 to lower limb amputations (Dillingham et al., 1998). A similar ratio of upper to lower limb amputations can be found in the United Kingdom (U.K. Prosthetics Services, 2008). The major cause of lower limb amputations is related to dysvascularity, which affects mostly elderly people. Vascular problems requiring amputation are much less common in the upper extremities. The loss of an upper limb is most commonly caused by traumatic amputation, and amputees tend to be younger and in good health otherwise. The specific reasons of trauma-related amputations are diverse but the leading causes in industrialized countries include injuries involving machinery, powered tools and appliances, and motor vehicle accidents (Dillingham et al., 1998). Military conflicts are another source for traumatic amputations. Advances in the body armor of soldiers have increased the survival rate in armed conflicts, but also have increased the number of amputations due to severe injuries of the unprotected limbs (U.S.G.P.O., 2010). Cancer and infections are examples of further reasons for upper limb amputations but are not as frequent as trauma.

The length of the residual limb after amputation determines the options for prosthetic components and affects the potential for functional rehabilitation (Näder, 2011). The amputation levels for upper extremities include (Fig. 14.1): upper digits and partial hand, trascarpal, wrist disarticulation, transradial (below elbow), elbow disarticulation (transection through the elbow joint), transhumeral (above elbow), and shoulder disarticulation (transection through the shoulder joint). Finger and partial hand amputations, transradial amputations, and transhumeral amputations are the most frequent amputations. From the 215 upper limb referrals reported by the U.K. Prosthetics Services (2008), 44% were more distal or equal to wrist disarticulation, 18% were transradial, and 25% were transhumeral.

As a general rule, the residual limb should be as long as possible. The longer the residual limb, the better is the leverage for lifting, pushing, and pulling activities, and the more sensory information and residual muscles are still available for moving and controlling the prosthesis (Näder, 2011). Conversely, higher amputation levels require prostheses of additional complexity (more joints), but the control options are reduced. In the case of a distal transradial amputation (long transradial amputation), for instance, hand and wrist are replaced by prosthetic components, but a large part of the arm, including

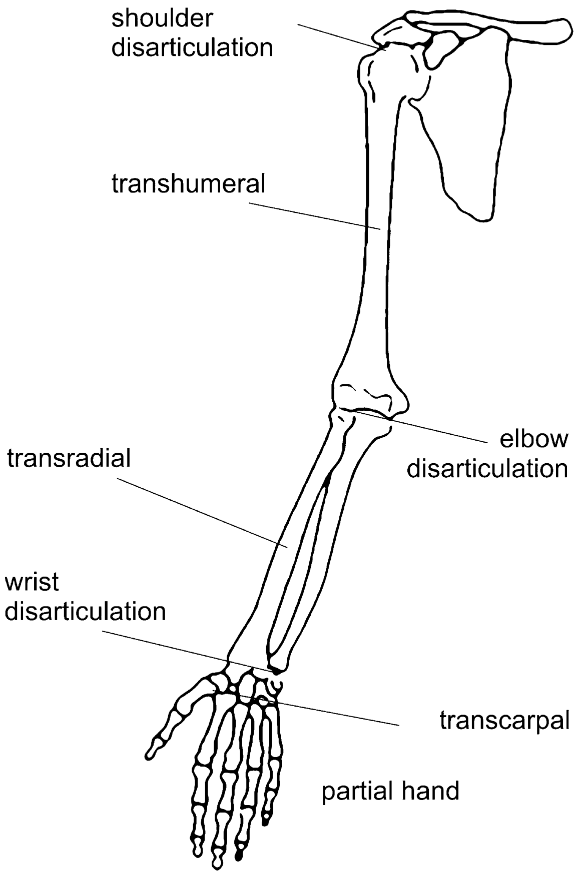

Figure 14.1. Upper limb amputation levels. (Modified from H.G. Näder, 2011.)

residual forearm muscles, is still available to use the prosthesis. Most of the wrist rotation capability (pronation and supination) is still preserved at this level. In a short transradial amputation, however, this capability is not available anymore. As another example, amputees with shoulder disarticulation would need a prosthesis that substitutes the entire arm including shoulder. The complexity of such a prosthesis is considerably higher than in, for instance, the transradial case, since all the structures, motors, and sensors (bones, muscles, and receptors) of the arm are lost. A prosthesis of this amputation level has to provide the functionality of a transradial prosthesis as well as elbow and shoulder functionality.

Most amputees suffer from a unilateral amputation. Those with a high-level bilateral amputation such as bilateral shoulder disarticulation amputees present the greatest challenges for functional restoration. The need for functional restoration is enormous, since many essential activities of daily living

(ADL) cannot be carried out independently. Even for the most basic and personal tasks such as dressing, eating, and performing personal hygiene, the bilateral amputee depends on the help of others when an appropriate rehabilitation by prostheses is not attained.

The purpose of a prosthesis is to improve the appearance and to provide the ability to perform tasks of daily living and increase quality of life. Amputees have to benefit from their prostheses. If function, comfort, or appearance is not sufficient, amputees will not use the device. According to several researchers (Biddiss and Chau, 2007; Schultz et al., 2007; Atkins et al., 1996), the two most common reasons for not using a prosthesis are the lack of functionality and discomfort. Unfortunately, function, comfort, and appearance often conflict with each other. Prostheses that have a very natural appearance are often limited in their functionality, while highly functional devices may look unattractive or are heavy and therefore uncomfortable.

Depending on the level of amputation, upper limb prostheses may comprise a terminal device, wrist unit, elbow system, shoulder joint. Of special importance is the **socket**, which is the interface between the amputee's body and the prosthesis. It has to remain attached (suspended) to the residual limb for the entire range of motion, and it has to allow the load required for performing ADL tasks. Depending on the amputation level and the residual limb condition, fitting a socket can be a challenging task. It is important to note that the most versatile and advanced prosthetic components are useless when the socket interface is not well fitted to the amputee. There are three broad categories of upper limb prosthesis: passive, body-powered, and externally powered. Figure 14.2 depicts examples of these three different types. Passive prostheses provide cosmetic restoration, but do not provide active grasping capabilities. Natural appearance and lightweight design are the main advantages. Modern materials allow texture, skin tone, superficial veins, and other structures to be individually optimized to the amputee's needs, making it very difficult to tell apart from the natural hand. Body-powered prostheses are controlled by body movements such as gross shoulder movements. A harness-and-cable system captures these movements and actuates one to three degrees of freedom (DOFs) of the prosthesis. This design is very durable and has only moderate weight. Another advantage is the feedback that is provided to the user by the cable tension. Through this feedback the user can get a sense of the position or state of the terminal device. The disadvantages include rather limited grip force, uncomfortable harness, required energy expenditure, unnatural appearance, and additional loading of the shoulder joint.

Externally powered prostheses contain actuators that are driven by electrical, hydraulic, or any other power source external to the body. Although the power source is external, it has to be wearable and contained in the prosthetic system. Almost all externally powered prostheses available today use electric motors and rechargeable batteries. Compared with body-powered prostheses, these prostheses are heavier, more costly, and do not provide any somatosensory feedback other than the very rudimentary feedback provided by the

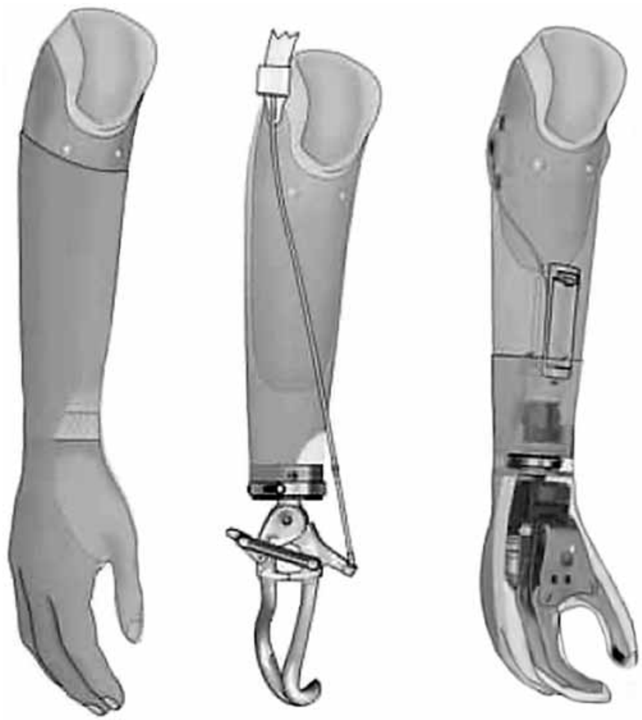

Figure 14.2. From left to right: passive (cosmetic) prosthesis, body-powered (cable-driven) prosthesis, and externally powered prosthesis with indicated cosmetic cover. (Modified from H.G. Näder, 2011.)

socket–stump connection. Externally powered prostheses, however, offer superior grasping force, responsiveness, speed, and, most important, a large variety of control options. Push-buttons and harnesses with switch or linear transducer mechanisms are simple forms of controlling such devices. The most common means of controlling this type of prosthesis is **myoelectric control**, which is derived from muscle signals generated by voluntary muscle contractions. These signals are typically recorded from surface electrodes located in the prosthetic socket and placed over the residual muscles of the amputee's stump. Current commercial systems allow the control of only one DOF at a time, for instance, hand opening or hand closing. However, advances in human–machine interfaces based on myoelectric signals or invasive approaches utilizing signals from the nervous system directly do offer considerable improvements.

In the following sections, we give an overview of the current state of the art of commercial externally powered prostheses and outline current developments in research that will most likely have an important impact on future commercial prosthetic systems. We present the requirements of advanced prostheses and discuss the rather large gap between commercial systems and systems in academic research. Since the prosthetic hand is a key component in upper limb prosthetics, we mainly focus on prosthetic hands.

STATE OF THE ART

A prosthesis consists of several parts depending on the amputation level. Similar to the human hand, the prosthetic hand or the terminal device is the key element of functional performance for the upper extremity. The main task of the other parts of the prosthetic arm is to bring the terminal device in a suitable position for grasping and carrying out vocational operations and ADL tasks (Muzumdar, 2004). For this reason, terminal devices have a central role in upper limb prosthetics, and it is interesting to compare their capabilities with the human hand.

The Human Hand

Natural evolution has formed the human hand over millions of years. The result is an extremely versatile grasping and manipulation device with unmatched dexterity, reliability, and durability. The hand is capable of performing a large number of activities ranging from simple to very complex tasks. Healthy people with natural hands can hold objects, change their position or orientation, and assess object features such as temperature or texture with a minimum of cognitive effort. These capabilities are based on a remarkably complex biomechanical system of bones, joints, ligaments, tendons, skeletal muscles, and sensors. Twenty-seven bones, more than 19 DOFs (depending on the mechanical model applied), and actuation provided by more than 30 muscles, many of which are not in the hand but in the forearm, form the hand–wrist complex (Changmok et al., 2008; Carrozza et al., 2006; Chappell et al., 2007). The large number of DOFs enables the hand to adapt to a wide range of objects that are different in size and shape. In addition, thousands of sensors measure a number of physical variables such as temperature, pressure, force, joint position, and sensations such as pain. These sensors together with the muscles are organized in a closed loop that is mainly controlled by the sensorimotor system of the brain (Bear et al., 2006). The computational complexity required is indicated by the large proportion of the somatotopic map on the cortex (homunculus) associated with the hand. In fact, it is the combination of the complex biomechanical system and the sophisticated control mechanisms that gives the human hand its capabilities.

Prosthetic Hands

Prosthetic hands that are currently on the market are unable to match even a small fraction of the abilities of the human hand. Most commercial systems provide only a very limited number of DOFs. Moreover, there is no system available that provides explicit somatosensory feedback to the amputee. Amputees can rely on the pressure on the residual limb exerted by the socket.

Experienced users may also utilize vibrations and mechanical noise produced by the prosthetic actuators. But these feedback mechanisms provide only a very poor substitute for the sensory capabilities of the natural hand. Therefore, amputees depend on visual feedback for positioning the limb and grasping objects. This has the consequence that amputees have to continuously monitor prosthetic activities, which requires much more selective attention and cognitive effort than when using natural limbs.

The task of a prosthetic hand is to substitute a lost hand. Therefore, one of the main requirements of a prosthetic hand is functionality. In addition to functionality, however, there are a number of basic requirements that prosthetic designs have to satisfy in order to be successful (Muzumdar, 2004; Biddiss, 2009; Pylatiuk et al., 2007). These requirements include compact and lightweight design, natural appearance, minimal power consumption, reliable and silent operation, and affordable costs. The prosthetic hand has to be an intrinsic design that also contains the actuators. Designs with actuators in other components of the prosthesis would limit the number of amputees who could use it. For instance, transradial amputees with an amputation level at the distal forearm could not use such a design. Moreover, all components of the hand have to fit into an anthropomorphic shape, because appearance is of great importance to amputees. Weight is another important feature. Since the weight of a prosthesis is concentrated at the socket interface, amputees prefer lightweight designs. An essential requirement, sometimes overlooked in research, is costs. The resources of healthcare systems are constantly decreasing. Insurance companies assess very carefully whether new expensive medical aids justify the additional costs compared with already existing less expensive solutions. Often the commercial viability of a medical aid depends on such cost units. When cost units are not willing to cover the expenses of a new advanced prosthesis, it may disappear from the market and consequently patients cannot benefit from the new development.

Current commercial prosthetic hands can be categorized roughly into two groups: Single-degree-of-freedom (1-DOF) actuator designs and multiple-DOF actuator designs. The 1-DOF actuator design has one DOF to open and close the hand with one grasping pattern. Since there is only one actuator, the actuator can be large, and therefore these hands are usually very robust, fast, and strong. In contrast, there is a new generation of commercial prosthetic hands that offer more than one actuated DOF and compliant grasping. Both groups, however, share the same control principles based on myoelectric signals, which will be explained later in this section.

The Otto Bock Sensorhand Speed (http://www.ottobock.com), shown in Figure 14.3, is a typical representative of the single-degree-of-freedom actuator designs to open and close the fingers and thumb. Many commercial prosthetic hands have such a design. Hands with a similar cinematic assembly are offered, for instance, by Motion Control Inc (http://www.utaharm.com) and RLSSteeper Inc. (http://www.rlssteeper.com). The grip pattern offered by the Sensorhand Speed is a tripod pinch grip with the thumb opposing the two

Figure 14.3. Otto Bock SensorHand Speed with an indicated cosmetic cover (left) and without cover (right). (Modified from H.G. Näder, 2011.)

fingers (see Fig. 14.3). The tripod pinch is one of the most common grasp patterns, and it also offers cylindrical grasp for wider objects (Muzumdar, 2004). The hand weighs 460 g and is very robust and durable. The maximum speed is 300 mm/s and the maximum grip force is 100 N. A number of myoelectric control options for discrete and proportional control using one or two bipolar electrodes are possible. To avoid allowing objects to slip, a sensor integrated into the thumb detects when a gripped object is about to slip, and the control system integrated into the prosthetic hand automatically adjusts grip strength so that the object remains securely in the hand. This intelligent behavior together with the speed and strength provided by this hand compensate to some extent the missing somatosensory feedback and the lack of a larger number of DOFs.

The Touch Bionics i-LIMB (http://www.touchbionic.com) is a new-generation prosthetic hand introduced just a few years ago. It was the first hand with articulated fingers on the market. Each of the five digits of the i-LIMB has two joints. Each finger is individually actuated by a micromotor contained in the finger. The thumb has an additional DOF for abduction and adduction. This motion, however, can only be performed passively. Due to the two DOFs per finger, the fingers can curve around an object. A control mechanism determines when each finger has achieved sufficient grip. Then the fingers lock in this position until the amputee triggers an open signal. The grip patterns offered by this hand include a key grip, a power grip, and a precision grip. Additionally, there is the finger-pointing grip with the index finger extended and all other fingers closed against the palm. To select a particular grip, the amputees have to manually rotate the thumb in different positions (Conolly et al., 2008). They can do that either with the healthy hand (in the case of a unilateral amputation) or by applying external forces such as moving the thumb against other objects. A similar prosthetic hand is the RSL Steeper, BeBionic hand (http://www.rslsteeper.com). This hand also offers fingers that are separately actuated and curl as they flex around an object.

The traditional 1-DOF prosthetic hands have rigid digits. Such digits cannot wrap around an object in a natural way. As a consequence, the contact areas between the objects and the prosthetic hand can be small. Due to the lack of friction and compliance the actuator has to provide stronger forces to ensure stable grasping. Hand designs with fingers that can wrap around an object and thus can spread the grip across a larger surface area may reduce the need for greater grip force (Carrozza et al., 2006).

Another new prosthetic hand that is about to enter the market (as of 2012) is the Otto Bock Michelangelo hand (http://www.ottobock.com). Its design is a trade-off between a fully articulated and a 1-DOF hand. It combines high strength and speed (grip force, 120 N; speed, 408 mm/s) with an increased number of DOFs and a set of additional compliance features. Each finger has its own motion axis (flexion——extension) defined by the joint that connects the finger to the metacarpus. The thumb has two perpendicular motion axes (abduction–adduction, flexion–extension). Thus the hand has 6 DOFs. Similar to the relaxed fingers of the human hand, all digits are slightly arch-shaped. This gives the hand a neutral look and appealing cosmetic appearance. The hand has two actuators. The main actuator provides the grasping motions. It drives flexion and extension of the thumb, index finger, and middle finger, which are mechanically linked. The second actuator, which is considerably smaller, drives the abduction and adduction of the thumb. These two separate motions of the thumb allow two different grasping patterns: tripod pinch and lateral pinch. Closing the hand while the thumb is in a palmar position simultaneously performs a finger adduction. This can be used to hold thin objects between the fingers, for instance, a paper or some bills. Moreover, the hand is equipped with compliance elements such as soft finger tips, passive finger movements in palmar direction (ring and little finger in all directions), and a force-balancing mechanism between the index and middle fingers. These elements may further increase the performance of this prosthetic hand in vocational and ADL tasks (Puchhammer, 2008). Figure 14.4 shows the Michelangelo hand and some of these compliance elements.

Although the new generation of commercial prosthetic hands offers more grasping options and compliance features, the performance of these hands is still very limited compared with the human hand. A number of intrinsic prosthetic hands developed in research provide a larger number of actuated DOFs, more grasping patterns, and various control mechanisms. Some of these hands even provide proprioceptive and exteroceptive sensory information. Examples are the Southampton-REMEDI hand (Light and Chappell, 2000), the RTR II hand (Massa et al., 2002), the MANUS hand (Pons et al., 2004), the Fluidhands (Gaiser et al., 2009; Schulz et al., 2005), the DLR hands (Butterfass et al., 2001; Liu et al., 2007), the Cyberhand (Carrozza et al., 2006),

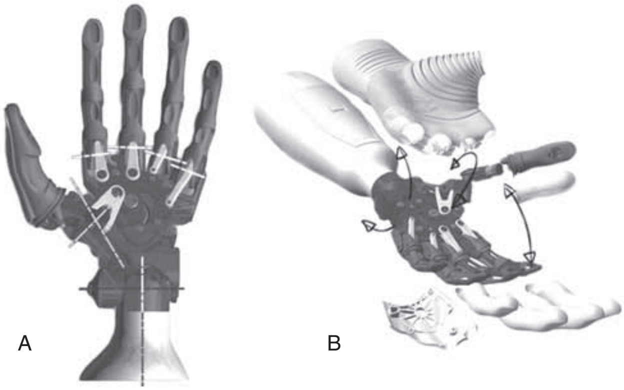

Figure 14.4. Otto Bock Michelangelo hand and wrist: (A) Dashed lines indicate joints and axes of motion. (B) The hand with compliance elements. Arrows indicate the possible motion directions of the digits. (Modified from H.G. Näder, 2011.)

and the Smarthand (Cipriani et al., 2009). A very recent hand is an 18-DOF intrinsic prototype hand developed jointly by the Rehabilitation Institute of Chicago, Otto Bock HealthCare, and Johns Hopkins University. It is designed to mimic the biomechatronic functionality of the human hand and to be robust enough to withstand the rigors of daily living (Weir et al., 2008). Although such multifunctional hands have the potential to provide amputees with improved prosthetic options, they depend on human–machine interfaces that can exploit the capabilities of these hands. Conventional myoelectric human–machine interfaces for prosthetic control, which will be explained in the next section, provide only very limited information transfer rates. That is, the number of commands that can be detected with sufficient accuracy and within a certain time frame is small. Controlling each actuated DOF directly with such an interface would be too cumbersome and unpractical.

Myoelectric Human–Machine Interfaces

Externally powered prostheses are typically controlled by myoelectric human–machine interfaces. Myoelectric signals (electromyographic signals, EMG signals) are the result of muscle contractions induced by motor commands generated in the central nervous system and sent to the muscles via the peripheral nervous system. For this reason, myoelectric human–machine interfaces can also be considered as neural human–machine interfaces (Ohnishi et al., 2007).

Conventional myoelectric control of prosthetic devices uses surface electrodes to record voluntary EMG signals. Although electrodes with electrode gel (wet electrodes) provide better signal quality, they are not an option in

Figure 14.5. Active bipolar myoelectric electrodes. These electrodes provide adjustable amplification and do not require gel or any special skin preparation.

prosthetic control, because they may dry out and are inconvenient to set up. Dry bipolar electrodes are typically used instead (Fig. 14.5). To achieve an acceptable signal-to-noise ratio, such an electrode not only picks up the potential differences from the skin, but also already amplifies them at the recording site (active electrode). Integrated into a socket, the electrodes are automatically placed over the residual muscles during the donning process. No particular skin preparation or manual electrode placement is necessary. However, the prosthetist has to take special care in the design of the socket to ensure consistent electrode positioning as well as reliable contact between the electrodes and the skin. The actual placement of the electrodes depends on the residual muscles, the condition of the residual limb, and the control strategy.

Common electrode configurations in commercial systems employ one or two electrodes. The two-site system uses two bipolar electrodes placed over the antagonistic residual flexor and extensor muscles. In cases where two sufficiently independent signals cannot be derived, for instance, due to a difficult stump condition, a single-site system is used (Muzumdar, 2004). Regardless of whether one or two site systems are used, conventional systems employ very simple signal processing: The signal is filtered to eliminate or reduce the influence of the power line and other external artifacts (noise). To have a measure for the muscle activity level, the mean absolute value or a similar estimate of the amplitude of each myoelectric signal is calculated. This signal feature is usually extracted by averaging (low-pass filtering) the rectified signal. Thresholds determined heuristically during the fitting or rehabilitation process define when a muscle contraction is detected. In fact, either the amplitude or the changing rate of the signal feature is used to detect appropriate muscle contractions (Muzumdar, 2004). All commercial myoelectric systems perform such or similar signal processing. Currently, there are no commercial systems available that can automatically determine the thresholds in an optimal and adaptive way to account for changes in the properties of the myoelectric signal.

Using this signal processing scheme, various control strategies are possible. In a single-site system, a simple switch (on/off) control can trigger hand closing or hand opening. In a two-site system, the contraction of the residual flexor muscles closes the hand; the contraction of the residual extensor opens the hand. The simultaneous contraction of flexor and extensor muscles, called a cocontraction, switches to another DOF; for instance, from the hand to the wrist. Then the contraction of the flexor or extensor muscle results in pronation or supination, respectively. When the amputee is able to voluntarily modulate the strength of the required muscle contractions, the speed and the strength of a prosthetic action (e.g., grasping) can be controlled proportionally to the amplitude of the myoelectric signal.

The control schemes just described require one or two largely independent EMG signals to control one DOF. Since there is a one-to-one association between EMG activity of one muscle (or muscle group) and the prosthetic command, these are **direct control** schemes. These control schemes, however, are not very suitable for prosthetic systems with more than two DOFs, because the number of independent EMG signals available is very limited. Although cocontraction of two muscles can be used to sequentially select different joints to be controlled, with more than two DOFs such sequential control becomes cumbersome, slow, error prone, and difficult for the user to learn. New approaches based on advanced signal processing and pattern recognition promise more independent control signals for improved prosthetic functionality (Englehart et al., 2000). However, at the moment there is no commercial system that utilizes these new approaches.

Targeted Muscle Reinnervation

Selective nerve transfer or targeted muscle reinnervation (TMR) is a new surgical procedure that has been successfully used to develop a clinically viable neural machine interface for people with high-level amputations. TMR is based on three facts (Kuiken et al., 2007): (1) The residual nerves of the peripheral nervous system that once innervated the amputated limb still carry the motor control and sensory information. (2) These nerves can be transferred to other muscles or muscle groups, and they can reinnervate these muscle. (3) After a rehabilitation period these residual nerves control the newly innervated muscles. The reinnervated muscles then have the role of biological amplifiers of the motor control information transmitted by the transferred nerves. Therefore, TMR provides myoelectric signals that are closely related to the myoelectric activity of the lost limb. In patients with shoulder disarticulation, for instance, the pectoralis ipsilateral to the amputation is typically selected for TMR. This is because this muscle is no longer biomechanically functional after the arm has been removed. Often the targeted muscle is surgically divided into several segments. Then the residual nerves (e.g., median, radial, ulnar, and musculocutaneous) are transferred to these segments. The purpose of this segmentation is to increases the independence of the muscle activity invoked by the transferred nerves. After rehabilitation, the muscle segments are reinnervated with nerves that once innervated the lost limb, and

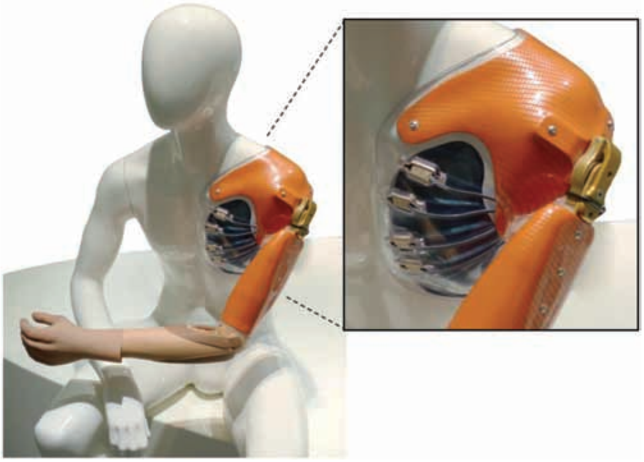

Figure 14.6. Example of a prosthetic fitting with a commercial TMR prosthesis (Otto Bock HealthCare Products GmbH, Duderstadt, Germany).

patients can produce muscle contraction patterns by attempting to move their missing limb. Advanced signal processing techniques are required to fully utilize these patterns and transform them into appropriate control signals for prostheses (Kuiken et al., 2007). However, TMR can provide enough independent muscle activity with sufficiently good signal-to-noise ratio so that even with simple direct control approaches a limited number of DOFs can be controlled simultaneously. In fact, TMR is already a clinically viable treatment for high-level amputees. It has already been successfully applied to more than 40 amputees with shoulder disarticulation and transhumeral amputation worldwide (Schultz and Kuiken, 2011; Kuiken et al., 2009; Dietl, 2008; Miller et al., 2008a,b). Figure 14.6 shows a prosthesis with three DOFs and direct control specifically designed for TMR patients. The selected nerve transfer is not limited to motor nerves. Targeted sensory reinnervation (TSR), which is the selected nerve transfer of sensory nerves, is also possible. It provides the patient with a sense of touch or vibration in the reinnervated area of the skin, for example, in the skin segments near or over the TSR site. Since the transferred sensory nerves are still mapped to the somatosensory cortical areas of the missing limb, the amputee perceives a stimulation of these areas as if the missing limb (phantom limb) were being stimulated (Marasco et al., 2009). More details about TMR and TSR can be found in Chapter 15 ("Myoelectric Prostheses and Targeted Reinnervation") of this book.

FUTURE DIRECTIONS

Technological advances in power sources, actuators, and transmission systems, as well as sensors and control systems build the mechatronic foundation for more functional and sophisticated prosthetic devices. The improved research funding situation for artificial limbs over the past decades, in particular in North America and Europe, has considerably increased the research interest in this field with a focus on mechatronics and neural–machine interfaces. Current anthropomorphic artificial hands in research such as those hands mentioned previously utilize these new technological advances. Despite this progress in research, these new dexterous devices are not yet clinically viable, mostly because they cannot be controlled satisfactorily by amputees. There are basically two ways to overcome this problem. One way is to increase the reliability and information transfer rate of the neural–machine interface. The other way is to develop new control strategies that employ more automatic control embedded in the prosthesis to reduce the attention required by the user. Such low-level control mechanisms are already available to a limited extent in some of the commercial systems. For instance, the SensorHand Speed can adjust the grip strength automatically to prevent objects from slipping. As another example, the i-LIMB automatically performs a gripping pattern till sufficient grip is achieved and then locks the fingers. In both cases, no intervention from the amputee is necessary during these low-level control processes. Of course, the amputee has to initiate these control mechanisms by sending appropriate (high-level) commands over the human–machine interface, but then the action is performed automatically by the prosthesis. Future commercial prostheses may have more sensors and more low-level control algorithms and allow sophisticated combinations of high-level control by the amputee and low-level control by the embedded system. This "shared control" between amputee and prosthesis could be individually adapted to the needs of amputees (Micera et al., 2010; Cipriani et al., 2008). Amputees with limited high-level control capabilities (e.g., due to a difficult stump condition) could benefit greatly from the embedded low-level control. In contrast, amputees able to achieve sufficient information transfer rates with the available human–machine interfaces may feel more comfortable taking over most or even all of the low-level control by themselves. In any case, new mechatronic developments in prosthetics will have to satisfy the requirements mentioned earlier, and these new shared-control strategies will have to be intuitive or at least easy to learn. Although such approaches may depend a little less on efficient communication channels between amputee and prosthesis, there is no doubt that improved human–machine interfaces are of great importance for more reliable and functional upper limb prostheses. In fact, the lack of sufficiently powerful human–machine interfaces—or, more specifically, neural–machine interfaces—is the major limiting factor at the moment in upper limb prosthetics. Considerable research has been devoted to improving this situation by developing advanced signal processing methods and by designing new interface technologies.

Advanced Signal Processing and Pattern Recognition

Conventional direct control uses simple signal processing to calculate the amplitude or the amplitude change rate of the signals recorded. To work sufficiently well in terms of reliability and response time, this approach requires largely independent muscle activity. With surface EMG electrodes, only a small number of isolated EMG signals are available. Usually, only one or two electrodes are used with this approach in commercial systems. Even with TMR the number of independent signals may remain still too limited for controlling prostheses with a large number of DOFs by direct control. Advanced signal processing has the potential to extract more information from the recorded signals by decomposing these signals into components with increased independence, improved signal-to-noise ratio, and better spatial resolution. The goal is to transform the recorded signals into independent control signals that allow simultaneous and proportional control of multiple DOFs with a performance that is sufficient to carry out ADL tasks in an intuitive or at least easy-to-learn way (Parker et al., 2006).

Many different signal processing methods have been suggested since the early 1990s. Most methods require multivariate input recorded from a larger number of electrode sites. There are methods that transform the recorded signals into continuous control signals by employing linear or nonlinear transformations that are based on physiologically inspired models or derived from the recorded EMG signals by machine learning procedures (Englehart et al., 2000; Jiang et al., 2010; Ajiboye and Weir, 2009; Antfolk et al., 2010; Jiang et al., 2009; Muceli et al., 2010; Nielsen et al., 2011). Another group of methods categorizes the recorded signals into certain patterns that are generated by muscle activities. These pattern recognition methods transform the recorded signals not in continuous but rather discrete control signals (Oskoei and Hu, 2007). More information about these signal processing approaches can be found in Chapter 15 ("Myoelectric Prostheses and Targeted Reinnervation") in this book.

There are a number of methods that have achieved classification rates of more than 90% in classification tasks with up to 12 or even more classes. This might seem impressive at first sight; however, the clinical impact of pattern recognition approaches in prosthetic control is very limited. In fact, so far there is no commercial system available that makes use of these approaches. One reason for this unsatisfactory transfer from academic research to clinical practice can be explained by the fact that classification accuracy is the most often applied performance measure. Classification accuracy alone, however, is not sufficient for assessing the usability and clinical viability of a prosthetic system. More specifically, even high classification rates are not very meaningful if the controller is evaluated offline, no strict separation between training and testing data is performed, and signals are not recorded from amputees but rather from able-bodied subjects. Furthermore, many experiments reported in the literature were carried out under ideal lab conditions. These ideal environmental and experimental parameters are not available in practical applications. Signals are often susceptible to artifacts and their statistical properties are nonstationary; that is, they change their statistical properties over time. In fact, there are a number of ways signal parameters can change. The reasons include electrode impedance changes, mechanical displacement of electrodes, user fatigue, and user adaptation. New research efforts have been trying to increase the robustness and reliability of pattern recognition methods (Huang et al., 2010; Kaufmann et al., 2010; Hargrove et al., 2008; Scheme et al., 2010; Simon et al., 2009). One direction of research involves attempts to consider signal parameter changes in the *setup* of the classifier by including parameter variations such as electrode displacements in the training data (Hargrove et al., 2008). Another research direction investigates adaptive methods to alleviate the performance degeneration due to signal nonstationarities (Sensinger et al., 2009). The lack of adequate adaptive signal processing and classification is one of the limiting factors in the clinical applicability of pattern recognition approaches (Zecca et al., 2002). To be clinically useful, the algorithmic complexity of these methods has to be small enough so that they can run on embedded systems with modest computational power and memory resources. In any case more research is necessary before these methods will become available in commercial systems.

Advanced Neural–Machine Interfaces

Improved signal processing methods have the ability to increase the information transfer rate of human–machine interfaces. On the other hand, improved signal acquisition methods could simplify signal processing and increase the robustness of the overall human–machine interface. When the available information is limited by the signal acquisition method, then even advanced signal processing cannot improve much. This underpins the importance of effective and robust signal acquisition. With surface electrodes, for instance, the myoelectric signal of individual muscles can be difficult to record. Due to volume conduction and the simultaneous activation of muscles, a mixture of signals generated by different muscles is usually recorded from one electrode site. Although advanced multivariate signal processing can effectively reduce this cross talk, signal acquisition approaches that record closer to the signal sources may eliminate this problem completely. Moreover, the difficulties with establishing sufficient and consistent electrode contact, correct electrode placement, and the influence of other environmental factors could be eliminated or at least greatly reduced with invasive interfaces. In other words, invasive signal acquisition could solve many problems inherent in noninvasive approaches.

A number of interfaces with muscles or with the peripheral nervous system using different levels of invasiveness have been proposed (see, e.g., Micera et al., 2010; Yoshida et al., 2010; Navarro et al., 2005). Invasive myoelectric interfaces use either epimysial or intramuscular electrodes. **Epimysial electrodes** are placed on the muscle surfaces. **Intramuscular electrodes** are usually placed into the belly of the muscle. In contrast to surface electrodes, both approaches can record focal myoelectric activity from deep and small muscles. Fully implantable systems designed for prosthetic control using epimysial electrodes (Ruff et al., 2010) and intramuscular electrodes (Weir et al., 2009; Farnsworth et al., 2009; Light et al., 2002) are currently being developed.

To work, muscle interfaces require muscles or at least remnants of muscles that can still be activated to produce myoelectric activity. Depending on the amputation level and the condition of the residual limb, the number of suitable muscles can be insufficient. Targeted muscle reinnervation may be a solution for many of these cases, but interfaces to the peripheral nervous system (PNS) provide direct access to motor and sensory nerves. Since both afferent and efferent residual nerves remain intact long after amputation (Dhillon et al., 2004), interfaces to the PNS offer a bidirectional interface for control and feedback.

The design of electrodes is still an active area of research. Reliable electrodes are the key for the success of invasive human–machine interfaces. To be clinically useful, invasive electrodes have to be integrated into a fully implantable recording and stimulation system with wireless data transfer and power supply. Percutaneous systems for transmitting signals from the nerve to an external device are not an option, because of the risk of infections and wire breakage. In fact, the system has to be suitable for chronic, long-term, stable, maintenance-free, and safe implantation. It has to be fully biocompatible and mechanically robust, and the implantation procedure should be as simple as possible—ideally in a single surgical intervention. Before such invasive muscle or PNS interfaces will become common clinical practice more research and long-term *in vivo* tests are necessary.

Details about invasive interface technologies can be found in Chapter 4 ("Progress in Peripheral Neural Interfaces"), Chapter 5 "Multimodal, Multisite Neuronal Recordings for Brain Research"), and Chapter 16 ("Controlling Prostheses Using PNS-Invasive Interfaces for Amputees") in this book.

Sensory Feedback

As already mentioned earlier, visual information is the primary form of feedback in upper limb prosthetics. Visual feedback, however, often fails to reliably provide the information needed. Or at least, getting the required information by visual feedback alone may be cumbersome. For instance, the prostheses can block the view and compensatory movements are necessary to get the required visual information. As another example, a nontransparent container could contain a heavy load or could be empty, but visual information does not help to decide that. Applying sufficient grip for such an object can be difficult. Although local control mechanisms such as the one in the Otto Bock Sensorhand (see previous discussion) can help to prevent the object from slipping, sufficiently graded somatosensory feedback would be very important for intuitive prosthetic control. Sensory substitution, which replaces a lost sensory modality with a still existing modality, is one possible solution to close the feedback loop more explicitly than in current prostheses (Lundborg and Rosén, 2001). Noninvasive techniques for applying vibration, pressure, temperature, and electrical stimulation have been suggested to induce feedback (Micera et al., 2010; Antfolk et al., 2010; Rosén et al., 2009). These techniques try to map information such as forces and position captured by sensors in the prosthesis onto skin areas of amputees. Most often tactile feedback is induced. Proprioceptive feedback is more difficult to realize, but it would be important for more intuitive prosthetic control (Wheeler et al., 2010). In any case, unnatural feedback modalities and sensory substitution requires training. The amputees need to learn to interpret the unnatural stimuli and correctly map this feedback to the information it represents. Targeted sensory reinnervation (TSR) has the potential to simplify this learning process. In TSR, afferent nerves that once innervated the lost limb are redirected to previously deinnervated skin areas in or near the residual limb (Kuiken et al., 2007; Marasco et al., 2009). After the reinnervation process, sensory information from these areas is linked to the somatosensory areas in the brain that once were connected to the receptors in the missing limb. As a consequence, when these areas are mechanically stimulated, the amputee perceives the sensation not on these reinnverated skin areas but in the missing limb (phantom limb). TSR may, therefore, be used as a noninvasive portal to the sensory system to provide intuitive sensory feedback to the users of prostheses. Invasive interfaces that can directly connect to sensory pathways have the potential to provide a more selective feedback for both exteroceptive and proprioceptive perception. But as explained earlier there are many challenges to overcome before such invasive interfaces and the required electrodes will become clinical practice.

CONCLUSION

Over the last decades, advances in commercial prosthetics for upper limbs have been modest. The designs of body-powered or externally powered commercial systems have changed very little for a long time. New materials, rechargeable batteries with enhanced energy-to-weight density, and increasingly powerful actuators have led to redesigns of the established prosthetic components. These incremental design improvements have resulted in stronger and faster prosthetic components with improved durability, but they have not significantly changed the functionality, or the degrees of freedom, or the way these prostheses are controlled. Only recently have new commercial prosthetic developments such as the Touch Bionics i-LIMB or the Otto Bock Michelangelo hand become available. Although these new prosthetic hands offer more DOFs, increased functionality, and compliance components, their control mechanisms based on surface myoelectric signals are still very similar to conventional systems. That is, only one DOF at a time can be controlled, and controlling more than one DOF is cumbersome and difficult to learn.

New research efforts supported by increased funding opportunities over the last years have suggested a number of ways to improve the current state of the art in commercial systems. The possible solutions include shared-control approaches, advanced signals processing, selective nerve transfer, new signal acquisition methods, and methods for providing somatosensory feedback. A key component of advancing the state of the art is the human–machine interface for controlling the prosthetic device. Different invasive and noninvasive approaches have been investigated, with promising results for all levels of amputation. However, many of these new technologies still require considerably more research to evaluate and improve reliability and long-term stability. Most of the results have been achieved in lab environments under ideal conditions. To determine the advantages of a new approach and, most important, its clinical relevance and benefit for the amputee, extensive testing in realistic environments with practical evaluation protocols and comparable performance measures is required. Additional research is needed to determine the best methods for validation. Standardized performance measures for prosthetic devices are required to objectively compare the efficacy and clinical success of new approaches. Such performance measures are also needed to justify the increased costs of new developments. Given the rather small number of upper limb amputees and the complexity of the advanced solutions discussed in this chapter as well as the excessive costs for clinical evaluation, there is no doubt that prosthetic products based on these technologies will have to be expensive. Insurance companies will very carefully assess these products, and they will only cover the expenses when the ratio between costs and clinical benefit is appropriate. Often the commercial success—and thus the viability and availability of a prosthetic device—depends on the willingness of insurance companies to pay for it. Consequently, new prosthetic products have to be both clinically and commercially viable.

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