The *Science* in Science Fiction's Artificial Men

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Bioengineers are working around the clock to meet science fiction's standards for electronically powered artificial limbs. Combining state-of-the-art embedded systems and real-time software solutions with some innovative bio-interfacing strategies may just meet the challenge. Science fiction has plenty of fantastic examples of humans made from artificial parts: Star Trek*'s Lieutenant Commander Data and* Star Wars*' villain Darth Vader stand out among them. Data, controlled by his positronic brain, is a full-fledged android. Vader, on the other hand, remains some part human, although the ominous mask he wears is a constant reminder of the artificial components he must don to stay alive. From the perspective of the storytellers, we have mastered the science of mimicking humans with technology. Such artificial humans are effortlessly woven into these fictional storylines which leave reality with the daunting, complex task of actually engineering such achievements. With a quick trip to the lab, Luke Skywalker is fitted with a fully functional artificial hand to replace the one he lost in a battle against Darth Vader. Compared to Vader or Data the android, Skywalker's hand seems almost trivial ... in fiction maybe, but reality tells a different story.*

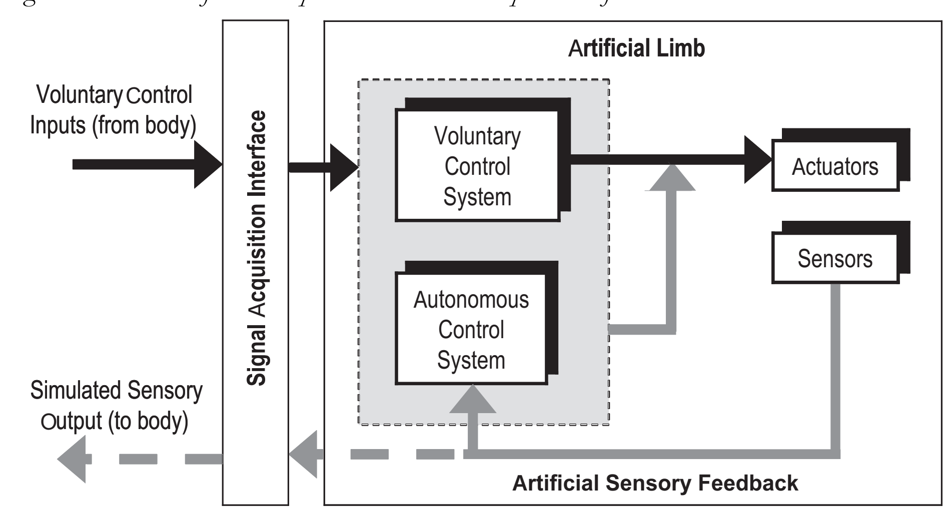
Although Luke Skywalker's hand seems trivial compared to the technology used for Lieutenant Commander Data and Darth Vader, compared to modern technology, it emulates our current efforts to create a synthetic, symbiotic robotic arm.

Figure 1 depicts an overview of the components necessary to make up an artificial limb such as the one used to replace Skywalker's hand. At the heart of this system are the voluntary and autonomous control components, generally encapsulated in a coordinated digital signal processing (DSP) microcontroller and capable of real-time processing. These two components control the functional branches of the system as shown by the black and gray arrows.

The first branch, indicated in black, allows the user control over basic motions required of the limb, for example, grabbing an object. The second branch, indicated in gray, allows the limb to autonomously fine-tune its activities based on sensory feedback made available to the system through sensors within the limb itself. This functionality is more subtle than voluntary control because it usually goes unnoticed when we do it with a natural limb. For instance, when we grab an egg, we do not think about how hard we should grasp. Instead, our nervous system automatically takes care of that for us so that we can grab the egg without breaking or dropping it. The dashed gray arrows indicate a sub-branch of this function, allowing users to be made aware of the sensory feedback provided by the hand. For instance, we can feel when our grasp is slipping in a natural hand, and a fully functional artificial hand should provide a similar function.

Modern developments in microcontroller, micromotor, and microsensor technologies yield promising avenues for continued development of the front-end actuation and fine-tuning efforts necessary for a fully functional artificial limb. The real challenge for bioengineers pioneering this technology is the back-end voluntary control and sensory perception function. Moreover, the challenge becomes even more daunting as the degrees of freedom for the artificial limb increase, yet the solution becomes more essential for the user.

Figure 1: *Overview of the Components That Make Up an Artificial Limb*



Conventional Control Systems

Myoelectric control has found widespread use as a voluntary control strategy in upper-limb powered prosthetics. Using this approach, voluntarily controlled parameters of electrical signals from muscles are used as inputs to modulate prosthesis function. These electrical signals, which can be measured noninvasively by a pair of electrodes placed on the surface of the skin, are called myoelectric signals.

Early myoelectric controllers operated in an on/off mode to control prosthetic function. For instance, when the controller detected a signal from one muscle, it opened a prosthetic hand; when it detected a signal from another muscle, it closed the hand.

This simplistic control scheme is easy to implement in either analog circuitry or digital software, requiring only an estimate of the mean absolute value of the signal to compare to an on/off threshold. While simple, this control scheme is substantially limited since any additional functionality is dependent on the availability of additional muscle sites for control inputs, and no provision is made for speed control. Furthermore, electrode placement to pick up single muscle signals is challenging, and voluntary contraction of the single muscles is often non-intuitive and difficult for users to learn. Consider, for instance, using the biceps and triceps muscles in the upper arm to open and close a hand. Nevertheless, artificial hands with such limited grasping functionality were making significant clinical impact by the 1970s and well into the 1980s [1]. The Otto Bock 2-state system was a common example [2].

The evolution of microcontroller technology including DSP chips with real-time processing power offered new opportunities for advancing powered prosthetic development. As microcontroller technology evolved, more sophisticated control schemes based on complex pattern recognition became possible. Research into the nature of the myoelectric signal has demonstrated that a given muscle within a muscle group will contribute variably to the overall group's signal depending on the intended limb action [3]. The sum of the contribution of all muscles within a muscle group will, therefore, reflect intended action-dependent patterns. Because of the random nature of the myoelectric signal, these patterns are difficult to extract, but with the advent of DSP chips like Texas Instrument's C2000 – found in the Boston Elbow developed by Liberating Technologies Inc. [4] – software that reliably interprets these signals can be embedded into the artificial hand's control system. Different classification strategies are currently being investigated including statistical; syntactic; and, most recently, machine learning via the perception-based neural network [5].

Increased computational resources and advancements in algorithm development have afforded bioengineers opportunities to explore some rich feature sets for input to the pattern classification software. Early pattern classification-based control systems were limited to simple-to-calculate time domain signal statistics such as variance, zero-crossings, and waveform length to represent the myoelectric signal of interest [1]. Now, far more computationally complex feature sets are being investigated, including autocorrelation coefficients; spectral measures; time-series model parameters; and time-frequency coefficients based on wavelet and wavelet packet transforms and higher-order spectral analysis [1].

As an example, a pattern recognition based control system developed at the University of New Brunswick (UNB) was used to recognize 10 discrete movements

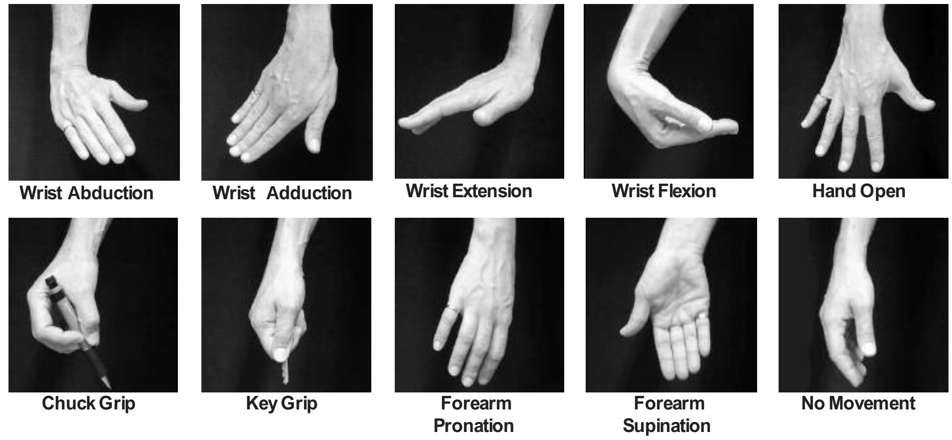


Figure 2: *Hand and Wrist Functions to be Restored in a Below-Elbow Amputee*

of the wrist and hand. This system would be used by an individual with an amputation below the elbow. The movements to be controlled are depicted in Figure 2.

Autoregressive coefficients and a linear discriminant classifier were used, and the system was trained for use by eight individuals. Sixteen electrodes were placed around the circumference of the forearm, as depicted in Figure 3. The performance of each subject was assessed by the percentage accuracy with which they were able to correctly select a randomly presented target movement. In Figure 4 (see page 6), the accuracy is shown for each subject with respect to the number of electrodes used[1]. Although performance varies between subjects, it is clear that the use of more electrodes yields better performance; no improvement exists beyond the use of eight electrodes. This system is remarkably accurate with an average user capable of selecting amongst these movements with an accuracy of 96 percent.

The pattern recognition strategy for voluntary control of powered prosthetics allows for more degrees of freedom than the simple, single-muscle/single-function control strategy because it can differentiate between many more intended limb actions. While this is an important step toward artificial limb technology which meets the standard of science fiction, real state-of-the-art systems are still limited. They are still dependent on the availability of muscle sites to elicit control signals, and they must control each joint in a serial manner; independent control of multiple joints is still an elusive task.

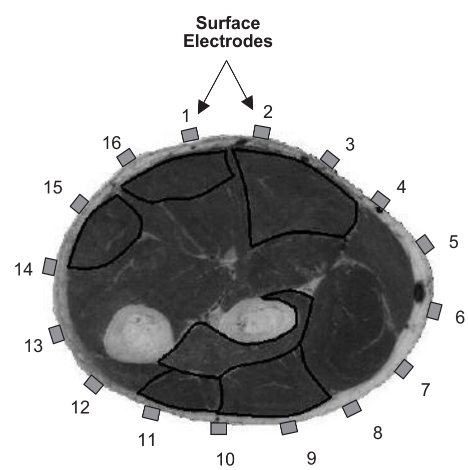
Emerging Strategies

Although steady progress has been made in myoelectric control systems, the use of the surface myoelectric signals in a conventional manner has inherent limitations. Individuals with high-level limb amputations (above elbow, for example) have few muscle sites from which control information may be derived, and they have more function which must be replaced. Consider an individual with an amputation at the shoulder. To restore lost function, the user must have a prosthesis capable of articulating many degrees of freedom, including the hand, wrist, elbow, and shoulder joints. The only myoelectric signals available for control are the pectoralis, some back muscles, and perhaps some remnants of the shoulder deltoids.

Therein lies a fundamental paradox: The higher the level of amputation, the more degrees of freedom must be replaced, with a diminishing number of control sites. Moreover, the available control sites are not physiologically appropriate; that is, the muscle activity bears no natural relationship with the lost degrees of freedom. Even the most sophisticated pattern recognition-based control system cannot defeat this paradox; only contrived contractions that are unrelated to the natural contraction patterns can be used to impart control.

The unfortunate consequence of this paradox is that those with high-level amputations are those in greatest need of

Figure 3: *The Placement of Surface Electrodes Around the Forearm*



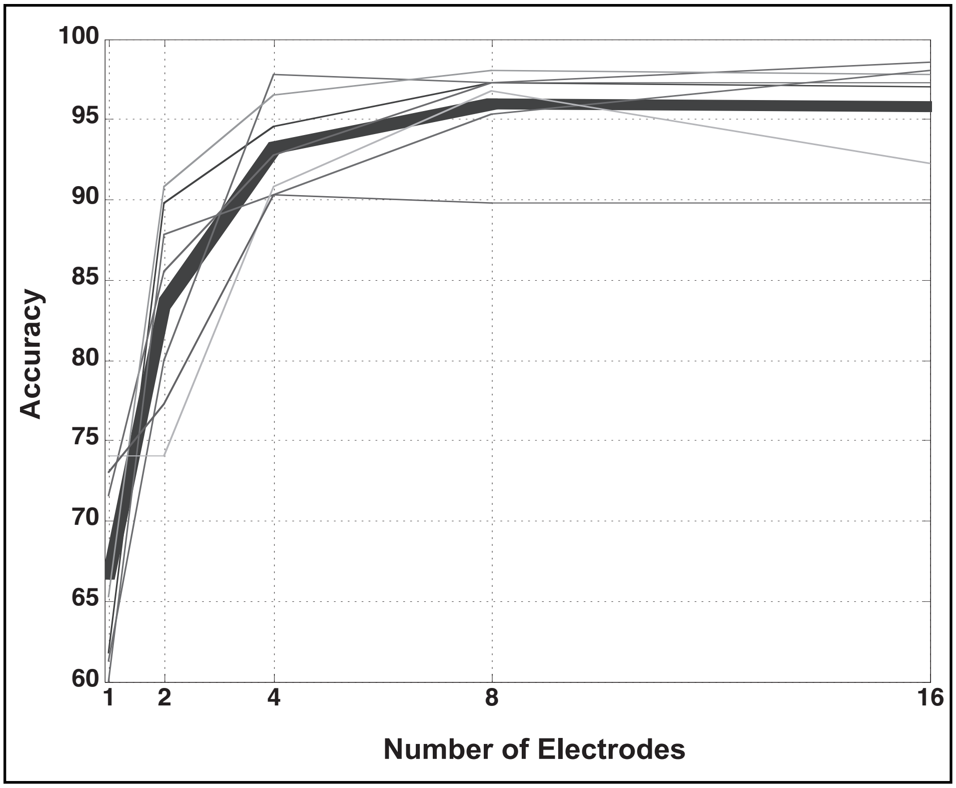


Figure 4: *The Accuracy of Each Subject in Selecting Between 10 Classes of Desired Motion. The Heavy Line Is the Average Performance Across All Subjects*

functional replacement. Individuals with a missing hand or wrist can perform activities of daily living quite well with or without a prosthesis. Those with amputation above the elbow or at the shoulder require substantially greater assistive augmentation.

The means of defeating this paradox lies in alternative sources of information. Clearly, the use of conventional myoelectric signals from residual muscle tissue cannot provide physiologically appropriate control sites. Fortunately, there are three emerging technologies that show great promise: Targeted Muscle Reinnervation (TMR), Peripheral Nerve Interfaces, and Cortical Interfaces.

TMR

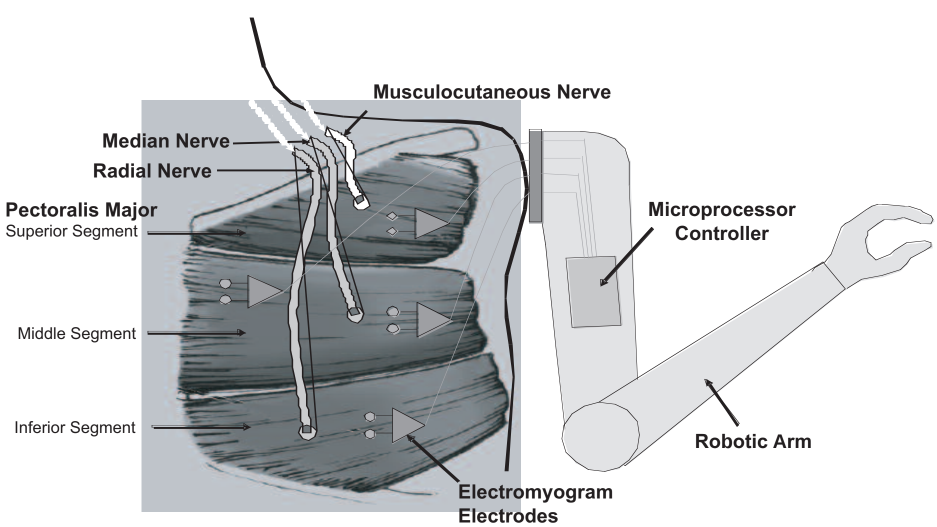
Often, residual nerves can remain intact after amputation and retain the capacity to transmit messages from the brain; they just do not have anywhere to transmit the information. TMR is a surgical procedure which transfers residual nerves from an amputated limb onto alternative muscle groups. The target muscles are not biomechanically functional since they are no longer attached to the missing arm. The re-enervated muscle then serves as a biological amplifier of the amputated nerve motor commands which are intuitively coupled to the intended action. The muscle thus provides physiologically appropriate, surface myoelectric control signals that are related to functions in the lost arm and allow simultaneous control of multiple degrees of freedom in an advanced prosthesis.

TMR is an innovative strategy for interfacing neural commands from the brain with an artificial limb. The artificial limb must still be fitted with an embedded system capable of supporting the software required to interpret the complex patterns in the myoelectric signal provided by the alternative muscles, and it must contain the software required to provide some simultaneous control which the input signals request. The intuitive nature of this voluntary control strategy makes TMR an extremely appealing development.

The first person to receive TMR was a 54-year-old male who had suffered severe electrical burns working as a high-power lineman in May 2001. He required bilateral shoulder disarticulation amputations [6]. To improve the function of his powered left prosthesis, TMR surgery was performed in February 2002. The patient's pectoral muscles were denervated, divided into four separate segments, and a residual arm nerve was transferred to each segment (Figure 5).

Within five months after the surgery, surface myoelectric signals could be recorded from the pectoral segments, re-enervated with the musculocutaneous, median, and radial nerves. In this subject, TMR allows the musculocutaneous nerve transfer to control elbow flexion, the radial nerve transfer to control elbow extension, the median nerve flexor region to control hand closing, and the median nerve thumb abductor region to control hand opening. Fitted with a sophisticated artificial arm that interfaced with the pectoral muscle group, the subject was able to operate his elbow, wrist and terminal device simultaneously with greater ease and speed.

Figure 5: *Schematic Description of Targeted Muscle Reinnervation Technique*[2]



Peripheral Nerve Interfaces

Peripheral nerves deliver control information to skeletal muscle. As compared to surface myoelectric signals, substantially more information about motor intent is available in peripheral nerves if it can be reliably measured. Unfortunately, nerve signals are much harder to measure, as they are embedded in the body and are surrounded by a muscle that creates an interference signal. Most artificial limb voluntary control systems have focused on myoelectric control inputs because no technology has been available to measure information from peripheral nerves. Recently, however, a great deal of research has been directed at measuring peripheral nerve activity using cuff electrodes that envelop the nerve [7], biocompatible silicon sieves through which a severed nerve may regenerate and clamps which compress the nerve, exposing multiple fibers to a recording surface [8]. Perhaps the most encouraging approach is the use of a slanted electrode array, developed at the University of Utah [9]. The Utah slant array is a 100-electrode array with a resolution of approximately 400 microns between electrodes, as depicted in Figure 6.

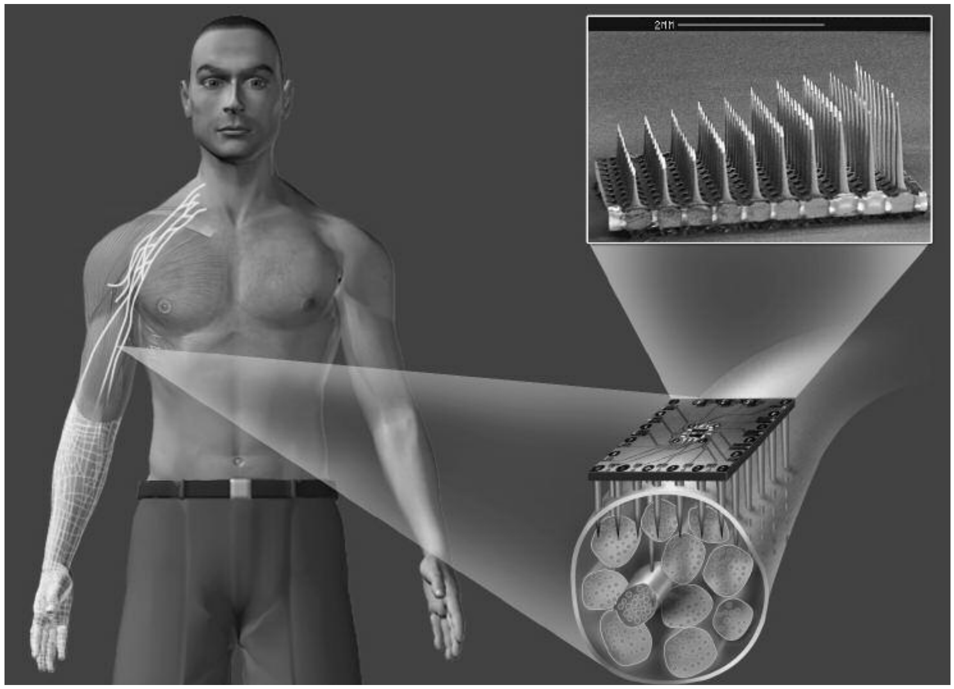


Figure 6: *The Use of the Utah Slanted Electrode Array in the Measurement of Peripheral Nerve Activity*[3]

Cortical Interfaces

Brain-Computer Interfaces (BCI) have been the subject of a great deal of research. An effective BCI would allow people with severe motor disorders such as paralysis, stroke, cerebral palsy, and spinal cord injury to control a device such as a robotic arm or a computer with signals recorded directly from their brain. Some promising advances have been made using surface electroencephalogram recordings [10]. Surface recordings require dozens of electrodes however and are therefore clearly not a practical approach for a system that a user must wear and maintain mobility.

Microelectrode arrays implanted in the motor cortex of monkeys have been shown to convey motor intent. Using this, it has been shown that it is possible to resolve cortical activity in a manner that describes limb trajectory and hand articulation [11]. Moreover, it has been shown that the pre-motor area of the brain can convey task-planning activities [12], which provides higher level information about motor intent. Although very promising, substantial biomedical challenges remain, such as implanting sensors in the appropriate locations, ensuring the biocompatibility, and powering these sensors for long periods of time.

Limb trajectory information from the motor cortex describes intent in Cartesian space (ordinary *two-* or *three-dimensional* space), with respect to the position of the hand. This is in contrast to the information from the myoelectric signal and the peripheral nerves, which impart control to the *joints* of the upper extremities. One may say that this information resides in joint space. A fusion of cortical information in Cartesian space and myoelectric signal/nerve signal information in joint space is likely the most robust approach to dexterous artificial limb control. With further developments in cortical interfaces, smart systems which integrate these information spaces may yield a fully functional, voluntarily controlled artificial limb.

With the promise of these new sensor technologies, new advancements in biosignal processing software will have to be made. New information extraction algorithms may have to be developed, along with new control strategies, and a viable means of sampling and wirelessly transmitting the high density stream of data to the front-end control system must be devised.

Pushing Forward

The U.S. Defense Advanced Research Projects Agency (DARPA) has sponsored two initiatives that address these emerging technologies described above, with the resolute goal of delivering next-generation prostheses to soldiers and civilians in the near term. A two-year project, entitled *Prosthesis 2007* has been awarded to Deka Research (Manchester, New Hampshire), which aims to dramatically improve state-of-the-art technology in upper-limb prosthetics. This will be accomplished by using existing technology or near-term innovation to produce a limb that will allow the user to simultaneously control his or her shoulder, elbow, wrist, and hand. A four-year project, entitled *Revolutionizing Prosthetics* has been awarded to the Johns Hopkins University Applied Physics Laboratory. This initiative will realize a prosthetic limb that has function identical to an intact human limb in terms of dexterity and sensory perception. In addition to meeting the challenges of deriving neural information from users for control, these projects will significantly advance prosthetics technology with regard to electromechanical design (energy storage, actuation, transmission) and human factors (improved socket design, osseointegration).

State-of-the-art, electrically powered artificial limbs are a long way off from meeting the standards set by science fiction. However, there is no doubt that we are now, more than ever, committed to meeting this challenge. Given the progress we have already made, new advancements in surrounding technologies, including embedded and real-time software systems and the resolve of the bio-engineers and medical practitioners working to meet the challenge, we are likely to see reality close in on fiction in the near future.◆

References

1. Parker, P.A., K. Englehart, and B. Hudgins. "The Control of Upper Limb Prostheses." Electromyography: Physiology, Engineering, and Noninvasive Applications. Eds. R. Merletti and P.A. Parker. Wiley-IEEE Press, 2004.
2. Scott, R.N., and P.A. Parker. "Myoelectric Prostheses: State of the Art." Journal of Medical Engineering and Technology 12 (1998): 143-151.
3. Hudgins, B.S., P.A. Parker, and R.N. Scott. "A New Strategy for Multi-function Myoelectric Control." IEEE Transactions on Biomedical Engineering 40.1 (1993): 82-94.
4. Murray, C. "Rewiring the Body." Design News Oct. 2005 <http://www.designnews.com/article/CA6275330.html>.

5. Englehart, K.S., B.A. Hudgins, and P.A. Parker. "Multifunction Control of Powered Prostheses Using the Myoelectric Signal." Intelligent Technologies for Rehabilitation. Eds. Horia-Nicolai L Teodorescu and Lakhmi C Jain. CRC Press, 2001: 1-61.
6. Kuiken T.A., et al. "The Use of Targeted Muscle Reinnervation for Improved Myoelectric Prosthesis Control in a Bilateral Shoulder Disarticulation Amputee." Prosthetics and Orthotics International 28 (2004): 245-53.
7. Strange, K., and J.A. Hoffer. "Restoration of Use of Paralyzed Limb Muscles Using Sensory Nerve Signals for State Control of FES-Assisted Walking." IEEE Transactions on Rehabilitation Engineering 7 (1999): 289-300.
8. Tyler, D.J., and D.M. Durand. "Chronic Response of the Rat Sciatic Nerve to the Flat Interface Nerve Electrode." Annals of Biomedical Engineering 31.6 (2003): 633-42.
9. Rousche, P.J., and R.A. Normann. "Chronic Recording Capability of the Utah Intracortical Electrode Array in Cat Sensory Cortex." Journal of Neuroscience Methods 82.1 (1998): 1-15.
10. Borrisof, J., et al. "Brain Computer Interface Design for Asynchronous Control Applications: Improvements to the LF-ASD Asynchronous Brain Switch." IEEE Transactions on Biomedical Engineering. 51.6 (June 2004): 985-992.
11. Schieber, Marc H., and Marco Santello. "Hand Function: Peripheral and Central Constraints on Performance," Journal of Applied Physiology 96 (2004): 2293-2300.
12. Musallam, S., et al. "Cognitive Control Signals for Neural Prosthetics." Science 305.5681 (2004): 258-262.

Notes

1. Initially, all 16 electrodes were used; to assess performance with eight electrodes, every other electrode was omitted. This procedure was used to assess performance with 4, 2, and 1 electrode.
2. Reproduced with permission of the Rehabilitation Institute of Chicago.
3. Reproduced with permission from the University of Utah and the Journal of Neurophysiology.

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