# Revolutionizing Prosthetics: Neuroscience Framework

Todd J. Levy and James D. Beaty

*The neuroscience framework, as applied to the process of controlling an artificial limb, consists of reading signals from the nervous system at several anatomical levels and integrating the signals to control movement. This is a key component of a strategy to provide robust control to a lifelike prosthetic limb. This framework, capable of running on an embedded processor, implements motor decoding, sensory feedback, and decision fusion algorithms to provide the link between the prosthetic limb and a user's nervous system. To accommodate various types of disarticulations and patient needs, the system is capable of processing signals from a variety of neural devices including muscle activity, peripheral nervous system action potential (spike) activity, central nervous system spike activity, and local field potentials for control and feedback. The flexibility of the neuroscience framework allows it to maintain a baseline level of control and provide risk mitigation in the presence of complications that will likely arise while working with human subjects.*

## INTRODUCTION

The vision of the Revolutionizing Prosthetics 2009 program is to create a neurally controlled prosthetic limb (PL) system that will restore significant motor and sensory capability to upper extremity amputee patients. This revolutionary prosthesis will be controlled, feel, look, and perform like a native limb to the extent possible with emerging technologies. To accomplish this, it is necessary to extract neural and other biological signals from the user.

Several types of recording devices are used to record various biological signals from muscles, peripheral nerves, and cortex for the purpose of motor decoding. Implanted intramuscular electrodes and surface electromyogram (EMG) electrodes are used to record muscle activity, implantable peripheral nerve electrodes intercept signals propagating along peripheral nerves, and implantable cortical electrodes capture spike and local field potential signals near their origins in the primary
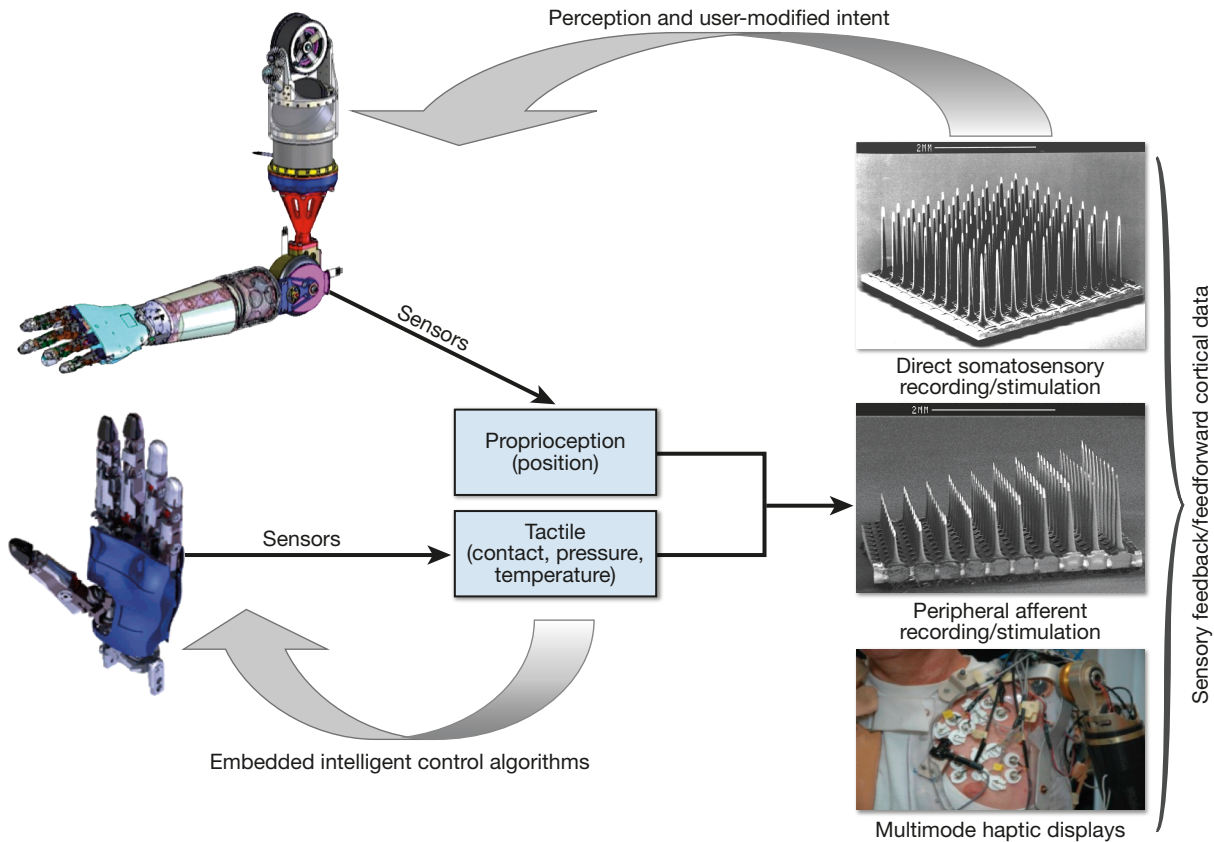
JOHNS HOPKINS APL TECHNICAL DIGEST, VOLUME 30, NUMBER 3 (2011)

**Figure 1.** Multimodal NI.

motor, premotor, and posterior parietal cortices. Collecting all of these signal modalities provides complementary information as well as a certain level of redundancy, providing the system with modularity and the ability to maintain a long-term, high level of fidelity. This is especially important because we are addressing the full range of amputees to include shoulder, transhumeral, transradial, wrist, and hand disarticulations in addition to normal interpatient variation. We have a robust neural integration strategy with a strong cortical focus and support for noninvasive or minimally invasive integration methods as well.

To enable safe operation of limb control and device management over the life of the system, the control system implemented within the neuroscience framework includes multimodal signal processing provisions and onboard monitoring capabilities (enabled by onboard 3-D accelerometers and limb position sensors), cross correlation of complementary data signals for performance integrity management, and integrated status monitoring.

In this article we discuss the neuroscience framework, which is an investigational framework for supporting embedded development on the PL and conducting experiments. We integrated data sets and corresponding algorithms from these "specifically focused" experiments using the "universal decoder" framework of the Virtual Integration Environment (VIE) (see the article by

Armiger et al. elsewhere in this issue). We also established recording array and integrated electronics for wired and wireless multichannel neural interface (NI) devices.

## THE NEURAL INTERFACE

The neuroscience framework targets the NI. The NI consists of cortical, peripheral nerve, and electromyographic recording devices; data acquisition and signal processing hardware that executes motor decoding and sensory encoding algorithms; and cortical, peripheral nerve, and haptic stimulation devices. The primary goal behind the NI strategies is to maximize the level of baseline control capability, over the long term, by accounting for known challenges up front and by establishing a device and system architecture that includes built-in provisions to accommodate a level of graceful degradation of signals while maintaining a high level of functionality.

The NI provides for bidirectional communications between the PL and the user's nervous system (NS). Output channels (NS→PL) are used to determine, on the basis of the observed neural activity, the user's desired movements for the PL. Input channels (PL→NS) are used to supply the user with sensory feedback from the PL by stimulating neural afferents. By enabling these feedforward and feedback pathways, the NI allows the
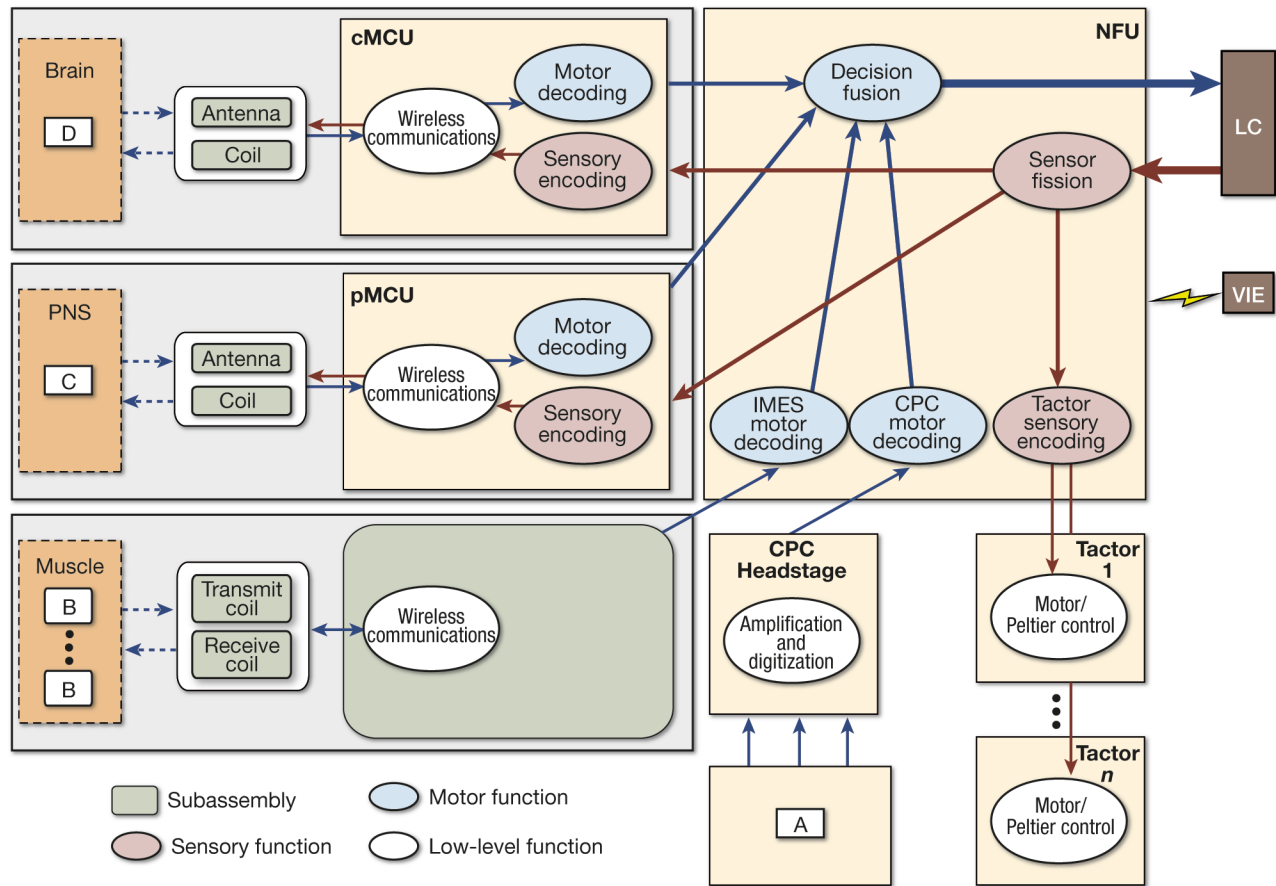
**Figure 2.** NI system architecture. CPC, conventional prosthetic controls; IMES, intramuscular electrical stimulation; LC, limb controller; PNS, peripheral nervous system.

user to obtain closed-loop control over the PL. A diagram of the NI is depicted in Fig. 1.

A block diagram of the NI system architecture is shown in Fig. 2. To accommodate users with different injury types, the NI system is designed to be modular. The Neural Fusion Unit (NFU) serves as the central communications and processing hub of the NI and is supplied with every NI configuration; attachments to the NFU provide additional functionality required to communicate with the user's NS through one or more available NI devices. Depending on an individual user's injury level, comfort with implanted systems, and willingness to undergo invasive surgeries, he or she can elect to use numerous supported NI devices alone or in combination.

Data flow through the NI is best described in terms of the feedforward and feedback pathways mentioned above. The feedforward pathway (blue circles and arrows in Fig. 2) is composed of four feedforward channels:

- "Noninvasive" surface EMG recording devices (A in Fig. 2)

- "Minimally invasive" implantable EMG recording devices (B in Fig. 2)

- "Moderately invasive" peripheral nerve recording/ stimulation devices (C in Fig. 2)

- "Highly invasive" cortical recording/stimulation devices (D in Fig. 2)

Each of these channels monitors one or more types of neuromotor activity and transmits this information to a local processing module—called a Multimodal Control Unit (MCU)—that can "decode" the data to determine which (if any) PL movements are desired by the user. There is a peripheral MCU (pMCU) and a cortical MCU (cMCU). The output from these local decoders takes the form of movement "decisions," which are combined within the NFU to generate a single output command to the PL called an "intent."

## IMPLEMENTATION OF THE MOTOR DECODING ENGINE IN THE VIE

The neuroscience framework implements the motor decoding engine within the VIE. Neural signals originating from both the cortex and periphery will be sampled in parallel using the system architecture in Fig. 2.
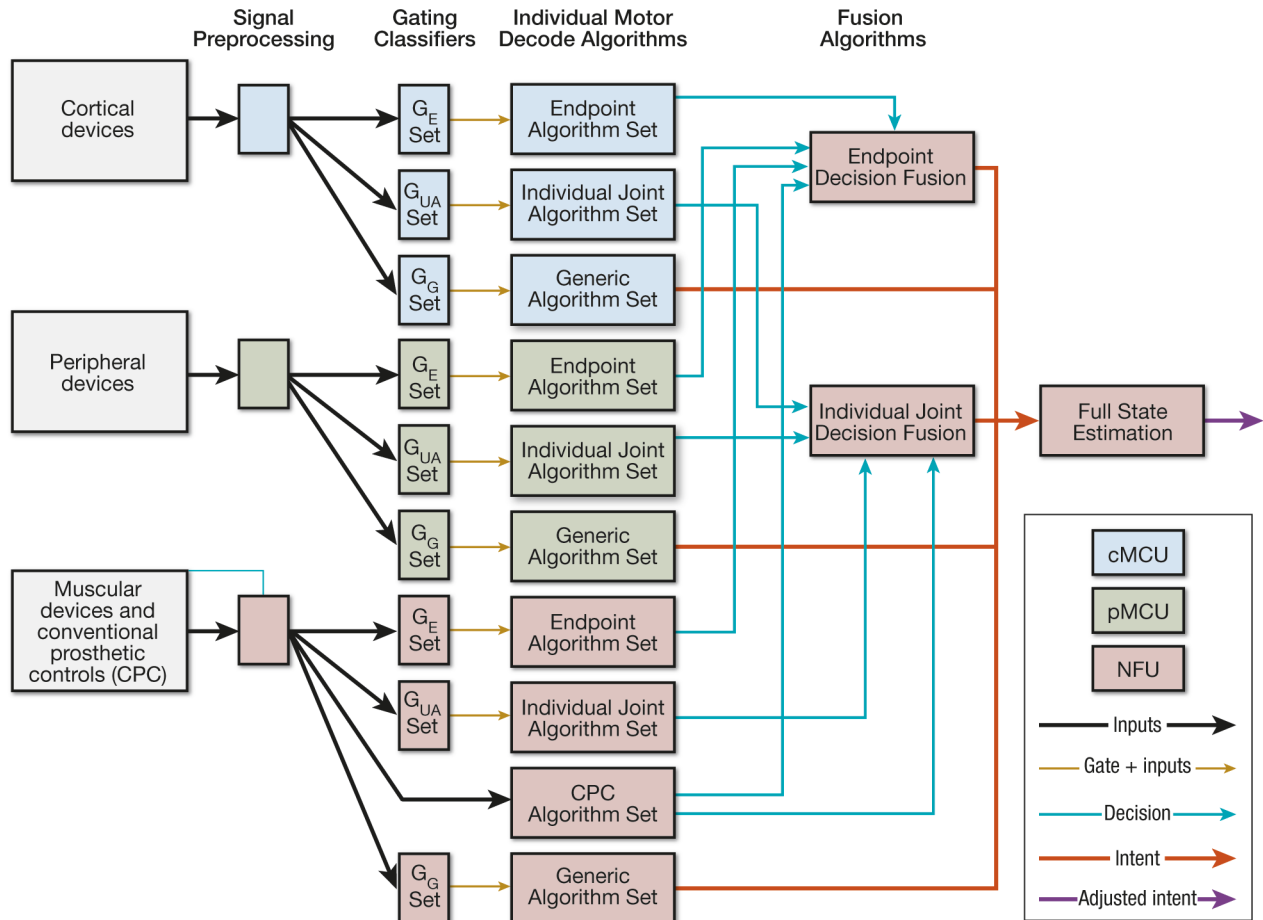
**Figure 3.** Overview of motor decoding engine. $G_E$, endpoint gating classifier; $G_G$, generic gating classifier; $G_{UA}$, upper-arm gating classifier.

These sensors will provide hundreds of signals that will be processed and fused together to intuitively control a PL. The motor decoding engine determines user intent based on the signal acquisition modalities fitted to a particular patient. This framework takes signals from the hardware, extracts relevant features, and determines moment-to-moment user intent. In some scenarios these signals will be synergistic and in others they will be conflicting, so the fusion algorithms are implemented to take advantage of synergies and resolve conflicts, resulting in optimal user intent. This decoded intent will then be sent as a command to the limb controller (LC), which will relay commands to actuators.

Because the overall NI is a modular system, the motor decoding algorithms must also be modular (Fig. 3). There are three processors on which algorithms run: the cMCU, the pMCU, and the NFU. The cortical MCU runs decode algorithms that rely on cortical input signals, the peripheral MCU runs decode algorithms that rely on peripheral nerve input signals, and the NFU runs decode algorithms that rely on EMG and conventional prosthetic control input signals as well as decision fusion algorithms.

The inputs to the decision fusion algorithms are the outputs provided by gating classifiers and individual decode algorithms. Gating classifiers are decoders that decode whether there is intended movement. This partitioning of functionality allows for efficient use of each processor and limits the bandwidth and power requirements of the MCU-to-NFU bus.

The decoders are transfer functions that map biological signals to user intent. Intent covers a wide range of control strategies such as individual joint angles and angular velocities, end effector position and orientation, and parameterized grasps. Several cortically based decoding algorithms that decode endpoint goal, endpoint trajectory, endpoint direction, finger movement, and grasp were developed by collaborators and by APL employees. Still other collaborators developed peripheral nerve signal-based algorithms that decode joint angle and finger selection. Many mathematical algorithms such as Kalman filters, Bayesian inference, artificial neural networks, linear discriminant analysis (LDA), and hidden Markov models were applied to decode intent. Later in this article we describe a surface EMG pattern recognition algorithm based on LDA that was developed at the
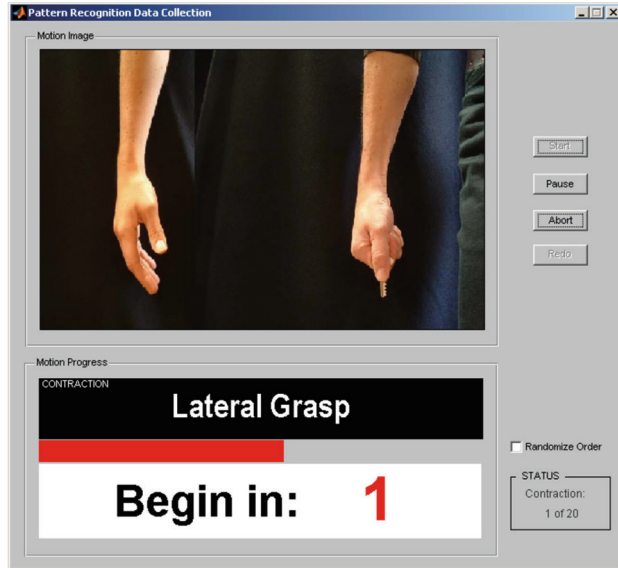
**Figure 4.** Training procedure.

University of New Brunswick. This algorithm was used extensively in clinical evaluations in conjunction with our first prototype limb with amputees.

Because decoders are designed to the common interface of the motor decoding engine, the modularity of this framework also accommodates future technology insertion. This approach allows for the direct and rapid translation of algorithms and methods demonstrated within the VIE into real-time experiments for demonstration of expected control capabilities (optimum and expected long-term baseline). In the Revolutionizing Prosthetics 2009 program, verification of signal acquisition locations and modalities, as well as algorithms, is performed at multiple institutions to ensure these new NI devices are safe and robust.

Many of the algorithms require supervised training. A graphical user interface, as shown in Fig. 4, assists with training by instructing the patient to attempt to move their phantom limb to specific configurations. Their neural signals are sampled while the patient is attempting those configurations, and a classifier that optimally differentiates them can be trained.

Many of the algorithms that were developed were optimized for previously recorded data sets. A subject makes motions while the neural signals are acquired. When the data set is played back offline, the algorithms decode the intent, which is known and used to evaluate the algorithm's performance. Because there is no feedback in this mode of operation, the algorithms are said to be running in an open loop. When the same algorithms are used online in a closed-loop mode of operation, there is visual and/or haptic feedback, which allows the user to alter their intent as they sense the limb moving or interacting with their environment. Sensory feedback usually has a profound effect on the performance of the algorithms. Current research into this phenomenon can be found in Ref. 1.

## DECODER DETAILS

The University of New Brunswick's surface EMG pattern recognition algorithm is an example of one of the decoders that was validated within the neuroscience framework. Figure 5 depicts the high-level data flow of pattern recognition of myoelectric signals (MES). A set of windowed time domain features are extracted from the raw MES in order to reduce the amount of data and maximize the information density. The features consist of the mean absolute value, the sum of the absolute value of the difference between data points, the number of zero crossings, and the number of slope sign changes for each EMG electrode channel. These features are fed into an LDA classifier (which consists of multiplication by a set of weights and addition of an offset), and the class with maximum likelihood is selected as the active class.[2] This is represented in the equation

$$g(\boldsymbol{x}) = \boldsymbol{w}^T \boldsymbol{x} + w_0, \qquad (1)$$

where $\boldsymbol{w}$ is a normalized weight vector, $\boldsymbol{x}$ is a feature vector, $w_0$ is a bias term, and $g(\boldsymbol{x})$ is the likelihood of a given class. (Note that vectors are bold in equations.)

The weights in LDA are chosen to maximize class separability. The University of New Brunswick's classifiers operate in the two-class case, where they choose the direction of motion: whether a joint is flexing or extending. The following derivation is modified from Ref. 3. The within-class scatter matrix is defined as

$$S_w = \sum_{i=1}^{2} P_i \Sigma_i, \qquad (2)$$

where $\Sigma_i$ is the feature space covariance matrix for class $\omega_i$ and $P_i$ is the prior of class $\omega_i$, and the between-class scatter matrix is defined as
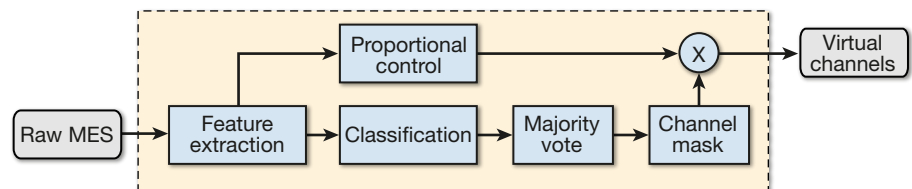


**Figure 5.** Single classifier pattern recognition flow diagram.

$$S_b = \sum_{i=1}^{2} P_i (\boldsymbol{\mu}_i - \boldsymbol{\mu}_0)(\boldsymbol{\mu}_i - \boldsymbol{\mu}_0)^T , \qquad (3)$$

where $\boldsymbol{\mu}_i$ is the feature space mean of class $\omega_i$ and $\boldsymbol{\mu}_0$ is the feature space mean of the marginal distribution over the classes. Using Fisher's Discriminant Ratio, which is

$$FDR = \frac{(\mu_1 - \mu_2)^2}{\sigma_1^2 + \sigma_2^2} , \qquad (4)$$

where $\mu_1$ and $\mu_2$ are the means and $\sigma_1^2$ and $\sigma_2^2$ are the variances of $g(\boldsymbol{x}) - w_0$ in class $\omega_1$ and class $\omega_2$, respectively, ignoring scaling factors, and making the appropriate substitutions, we arrive at

$$FDR(\boldsymbol{w}) = \frac{\boldsymbol{w}^T S_b \boldsymbol{w}}{\boldsymbol{w}^T S_w \boldsymbol{w}} . \qquad (5)$$

Maximizing the discriminant ratio yields the optimal weights,

$$\boldsymbol{w} = S_w^{-1} (\boldsymbol{\mu}_1 - \boldsymbol{\mu}_2). \qquad (6)$$

Thus, the classifier is $g(\boldsymbol{x}) = \boldsymbol{w}^T \boldsymbol{x} + w_0$, where

$$w_0 = \ln \frac{P(\omega_2)}{P(\omega_1)} \qquad (7)$$

and the class with the maximum $g(\boldsymbol{x})$ is selected.

The output is filtered using a "majority vote" algorithm, which acts as a low-pass filter to remove spurious decisions. The modified output is then used to create a set of "virtual channels" by assigning the channel associated with the active class a proportional value and assigning zero to all other channels via construction of a channel mask. The proportional value is derived from an estimate of the amplitude of the MES used to make the decision. This is done in order to model pattern recognition outputs in a way that mimics conventional MES channels as described in Ref. 4.

Figure 6 shows how the classifiers described above are combined in parallel. Each classifier is trained with its own input channels, weights, and offsets. At each time step, the output from each classifier is combined to form a final set of virtual channels.

The algorithm is conceptually simple, as is the implementation. The key to its proper function relies on proper signal acquisition and clinical configuration. In order for classifier outputs to be truly simultaneous and independent, minimal cross talk and coactivation must exist between classifier EMG sites. For example,
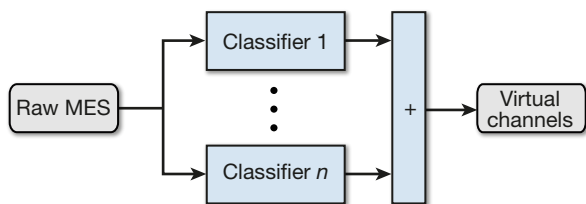


**Figure 6.** Parallel classifier flow diagram.

myoelectric activity at certain shoulder sites can be assumed to be relatively independent from activation of muscles in the forearm. Therefore, parallel classifiers could be used to classify hand and shoulder motions. However, this is of limited practical use given that a shoulder classifier would not be necessary if the forearm muscles are intact. This paradox limits the practical application of parallel classifiers in amputees unless the signals can be dichotomized.

Surgically, the targeted muscle reinnervation procedure has been shown to provide independent myoelectric control sites, thus making it a logical partner for use with parallel classifiers.[5] Because nerves are attached to separated sections of muscle, there appears to be less muscle coactivation. Although the relative proximity of control sites after targeted muscle reinnervation may cause some cross talk across recording sites, it is possible to "train out" some of this by including the motions of one classifier in the no motion class of the other(s). Tests with a targeted muscle reinnervation patient have shown the ability to control 3 degrees of freedom (hand open/close, elbow flex/extend, and humeral rotation) independently using three different parallel classifiers.

## DECISION FUSION

The key to intuitive use of a prosthetic and good algorithm performance use is the framework's ability to determine synergies and conflicts. For example, one set of signals may provide information about the intended hand grasp type, and another set of signals may encode the intended movement of individual hand joints. In these situations, algorithms embedded in the signal analysis framework must fuse the information in appropriate ways and send nonconflicting commands to controls. The other paradigm involves receiving two unique signal sets encoding conflicting movements of the same joint(s). The framework was designed to allow for resolution of these conflicts.

When designing frameworks there are two potential methods of avoiding conflicting commands. One method is to define decodes in such a way that conflicting commands can never be generated. For example, a decode may always decode only joint position and never explicitly decode hand grasp type. This method will be referred to as the global state framework. The second method is to use an algorithm that handles conflict resolution and determines when it is most appropriate to use certain decode strategies. This method will be referred to as the convergent framework. Decision fusion algorithms were used to implement this convergent framework.

It is important to note that one framework is not inherently more accurate than the other. A global state framework that decodes hand joint position could function as though hand movement had been decoded directly. In a convergent framework, when a grasp decode

is deemed more appropriate than a joint decode, a grasp decode that is modulated by signals encoding individual joint intent could be used. With this decode, the limb could traverse through the same set of states that it would under a very accurate global state framework.

## VISION FOR THE FUTURE

We will promptly transition subelements of the NI systems to human subject evaluations as individual wireless array components and corresponding regulatory approvals are available. These studies will validate that the individual components are functional in humans once the final, fully integrated NI systems are developed. Finally, we will converge the functional demonstrations from specific Internal Review Board studies with good-laboratory-practices-based animal research studies of fully integrated systems, design documentation, and design control provisions for a full Food and Drug Administration package. This will result in the submission of a complete Investigational Device Exemption application for the final limb.

For any NI strategy to be applied, the user and the Food and Drug Administration must have a reasonable level of confidence that there will be some baseline benefit as a result of implanting the NI devices and that this benefit will remain for a reasonable period of time. Establishing such a level of confidence is complicated in that there are inherent variables with all of the proposed interface methods. For example, experience with penetrating electrodes for the direct cortical interface has been well characterized. Complications may result from surgical placement and anchoring of the arrays; from

issues contributing to degradation of neuronal spike recordings over time; from relative device movement; from neural plasticity; from tissue response; from host/device interactions; and from many other factors. The primary goal behind the NI strategies is to maximize the level of baseline control capability by accounting for known challenges up front and by establishing a device and system architecture that includes built-in provisions for what may go wrong.

## REFERENCES

[1]Chase, S., Schwartz, A., and Kass, R., "Bias, Optimal Linear Estimation, and the Differences Between Open-Loop Simulation and Closed-Loop Performance of Spiking-Based Brain-Computer Interface Algorithms," *Neural Netw.* **22**(9), 1203–1213 (2009).

[2]Englehart, K., and Hudgins, B., "A Robust Real-Time Control Scheme for Multifunction Myoelectric Control," *IEEE Trans. Biomed. Eng.* **50**(7), 848–854 (2003).

[3]Theodoridis, S., and Koutroumbas, K., *Pattern Recognition*, 4th Ed., Academic Press, Burlington, MA, pp. 280–293 (2009).

[4]Meier, R., and Atkins, D., "Control of Powered Upper Extremity Prostheses," *Functional Restoration of Adults and Children with Upper Extremity Amputation*, Demos Medical Publishing, Inc., New York, pp. 207–224 (2004).

[5]Kuiken, T., Miller, L., Lipschutz, R., Lock, B., Stubblefield, K., et al., "Targeted Reinnervation for Enhanced Prosthetic Arm Function in a Woman with a Proximal Amputation: A Case Study," *Lancet* **369**(9559), 371–380 (2007).

# The Authors

Todd J. Levy

James D. Beaty

**Todd J. Levy**, an electrical engineer on the Revolutionizing Prosthetics 2009 signal analysis team, led the design and development of the decision fusion framework, a component of the neuroscience framework. Mr. Levy was previously an APL Associate Professional Staff member whose role was to develop for and support the VIE and work on various other signal processing-related tasks. He now resides and works in Massachusetts. **James D. Beaty**, Section Supervisor for the signal analysis team and Assistant Group Supervisor for the Biomedical Engineering Group, devised the concept for the neuroscience framework. Dr. Beaty was responsible for managing the development of the neuroscience framework and interfacing with collaborators that would be using it. For further information on the work reported here, contact James Beaty. His e-mail address is james.beaty@jhuapl.edu.

The *Johns Hopkins APL Technical Digest* can be accessed electronically at **www.jhuapl.edu/techdigest**.