

Development of Neural Network Interfaces for Direct Control of Neuroprostheses

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Abstract

This article describes technologies and strategies proposed for the development of prosthetic devices which would be directly interfaced to the nervous system. A chronic neural interface device is under development which should permit the establishment of permanent bidirectional communication with peripheral nerves in a human limb. An Artificial Neural Network would be used to interpret the neural signals and drive a prosthetic limb in the case of an amputation. For nerve repair in an intact limb, the neural network would be used to reroute misdirected signals into appropriate neural channels. Design considerations for the neural interfaces and supporting circuitry are discussed along with information processing strategies. It is intended that a fully integrated prosthetic device should be capable of adapting to the individual needs of the patient to provide a natural user interface.

1 Introduction

This article describes an ongoing project which is concerned with the development of neural interfaces to the human nervous system. Silicon based interfaces, perforated by arrays of via holes, are implanted between re-apposed ends of deliberately severed peripheral nerve fascicles. Regenerating axons grow through the holes and become physically isolated and spatially fixed with respect to the microelectrodes adjacent to each via hole. This should allow for permanent access to neural signals at or near the level of individual axons. An artificial neural network can then be used to interpret and process the information contained in the neural signals. To our knowledge, this is the first attempt to directly link biological neural networks to artificial neural networks. The artificial neural network, controlled by the central nervous system (CNS), would form a natural extension to the peripheral nervous system.

This article begins with a description of the silicon based neural interface itself, which is being developed by two of the authors (Kovacs & Rosen). The emphasis of this paper, however, is on the systems level considerations in designing a complete prosthesis and the role of neural networks in adapting the prosthesis to meet the individual needs of a patient. Two applications will be discussed. The first, is concerned with the use of interfaces to redirect neural activity in an intact arm so as to aid in the recovery of a severe nerve injury. The second deals with full limb prosthesis in the case of an amputation. A more comprehensive paper which addresses such issues as fabrication techniques, power dissipation, and biological feasibility, can be found in [1].

2 The Stanford/VA Neural Interface

This group has been working on a direct neural interface for peripheral nerves for several years under Veterans Administration funding¹. The goal of this work is to develop, largely by modification of existing commercial technologies, a microelectronic neural interface which will permit direct, chronic connection of electronic circuitry to the human nervous system.

¹Veteran's Administration Rehabilitation Research and Development (RR&D) Merit Review Grant B003 Hentz/Rosen "Towards Better Methods of Nerve Repair and Evaluation"

In order to achieve this goal, a microelectronic neural interface capable of repeatably sensing and stimulating action potentials in small groups or individual axons of peripheral nerves is under development. While a number of investigators have experimented with implantable nerve-regeneration type recording devices using semiconductor materials [2, 3, 4, 5, 6, 7, 8], this group would be the first to attempt chronic access at resolutions approaching individual axons, in addition to the use of active electronics in the implant itself.

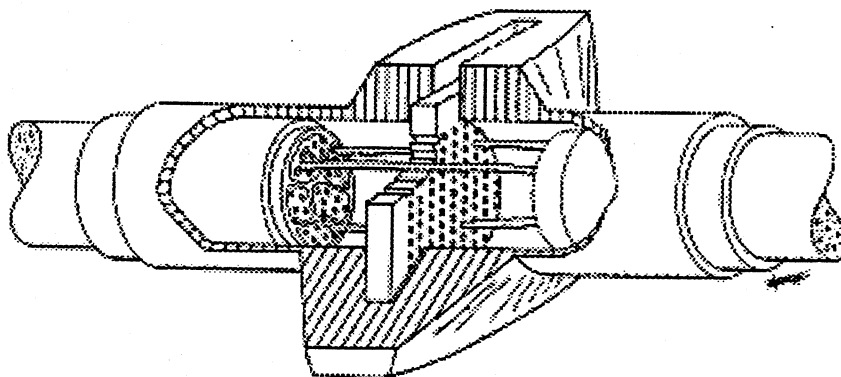


Figure 1: Drawing showing re-apposed ends of a peripheral nerve held against a microelectronic neural interface in a surgical coupler. Regenerated axons through the via holes in the silicon (not to scale) are shown in the cut-away view. (Reprinted with permission from [13].)

The current device, consisting of a silicon chip perforated by an array of via holes, will be held between the re-apposed ends of a deliberately severed peripheral nerve fascicle in a limb stump utilizing a surgical coupler (as shown in Figure 1). It has been shown experimentally [9] that for 8 to 12 μm via holes, individual regenerating axons will grow through the holes and become physically isolated and spatially fixed with respect to microelectrodes adjacent to each via hole. This arrangement will thus form a stable interface between the microelectronic circuitry on the neural interface device and the axons.

The present approach is to provide an individual neural interface for each fascicle of a major nerve. The design of monofascicular interfaces requires the use of approximately a 1 mm^2 surface area for the microelectrode array corresponding to each fascicle. The microelectrodes will be arranged in a two-dimensional grid at densities approaching those of the axons in peripheral nerves (1-2,000 axons per mm^2) to maximize access to the information present. The intimate contact of the microelectrodes with the axons should provide for good signal selectivity between microelectrodes.

Details on the development of specialized microelectrodes, surgical couplers, and fabrication processes, along with other technical and biological considerations can be found in earlier papers (see Kovacs et al [11, 12, 13, 14, 15]). It should be noted, that care was taken to utilize only processing techniques which are compatible with commercial CMOS fabrication so that the final arrays can be produced in a timely and inexpensive manner.

2.1 Preliminary *In-Vivo* Studies

A section of a blank neural interface (without microelectrodes or active microelectronic circuits) fabricated using a plasma etching technique [16] is shown in Figure 2. The blank neural interfaces were mounted in polycarbonate or resorbable GTMC (Glycolide Trimethylene Carbonate) surgical couplers and interposed between the surgically severed ends of rat and monkey nerves.

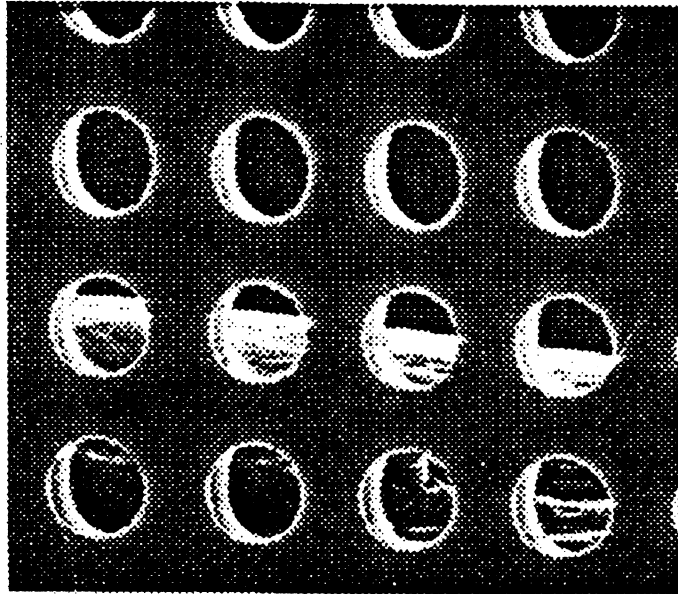


Figure 2: SEM (scanning electron micrograph) view of a section of a plasma etched blank neural interface (no microelectrodes). These via holes are approximately $12\ \mu\text{m}$ in diameter.

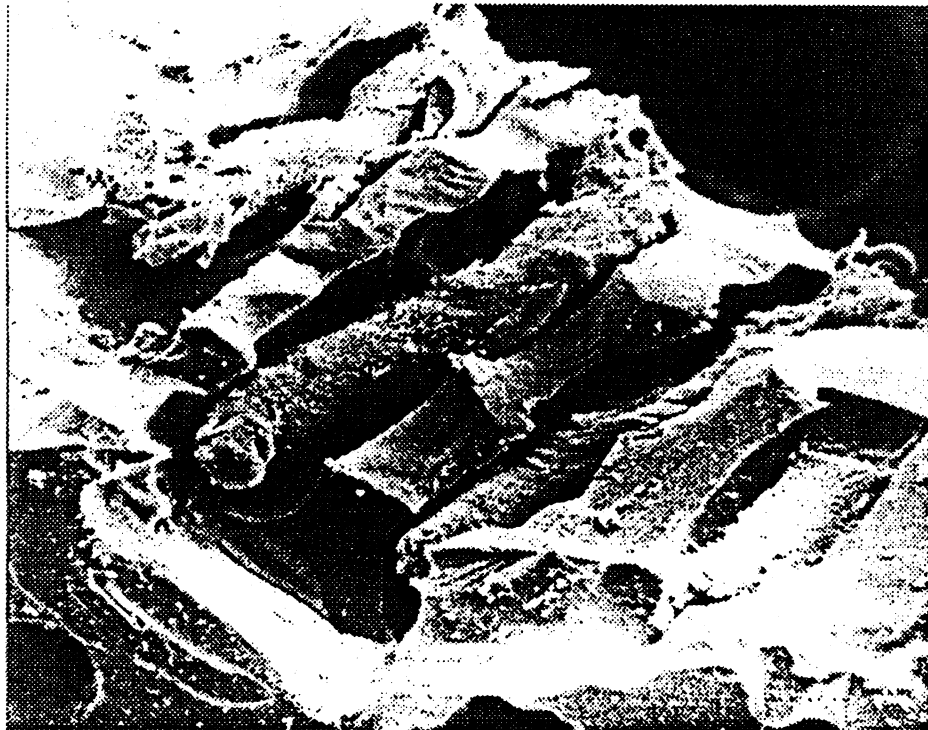


Figure 3: SEM view of monkey axons which have regenerated through via holes in a preliminary version (without microelectrodes) of the neural interface. (magnification = 1060X) Reprinted with permission from [12].

Using functional, electrophysiological and histological techniques, it was demonstrated that viable axons had regenerated through the via holes (see Figure 3).

2.2 Current Status of Neural Interface Research

Further work on the neural interface has been carried out, with the goal of incorporating the elements required to form a functional interface [11]. Passive neural interfaces (with microelectrodes but without active microelectronic circuitry) have been fabricated and implanted in the peroneal nerves of Sprague-Dawley rats [17]. Preliminary studies indicate that both recording and stimulating with the neural interface is possible [11]. Current work is focused on determining the degree of selectivity for each microelectrode site. As well, active neural interface prototypes have been fabricated which incorporate microelectronic circuitry to permit time-multiplexing of the neural signals in order to reduce the number of connections to and from the neural interface [13].

3 Nerve Repair

One of the originally envisioned applications for the neural interface deals with nerve repair in an injured arm. In a severe arm injury, it is often possible to surgically reattach main nerve bundles at the fascicle level. However, as individual axons regenerate a sort of *scrambling* occurs when the axons grow back to the "wrong" locations. The result is a severe functional limitation in an otherwise intact hand [21]. While therapy may result in increased usage, the process is time consuming and never complete. The use of neural interfaces, however, should allow one to electronically intercept misdirected efferent (motor) and afferent (sensory) neural impulses and reroute them into appropriate channels, thus "descrambling" the signals and providing increased recovery after a severe nerve injury. In order to block the original signals, two neural interfaces for each fascicle will be required (see Figure 4). Since fascicles contain both afferent and efferent signals each interface must be capable of either recording "incoming" signals or initiating "outgoing" signals.

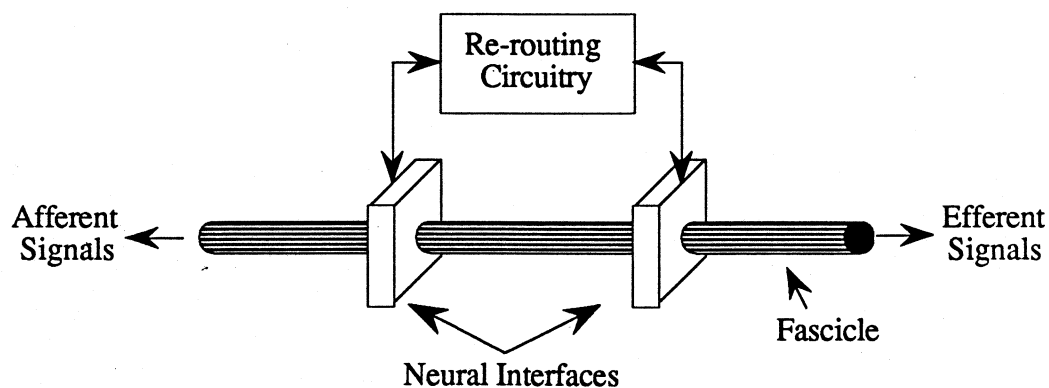


Figure 4: Diagram illustrating two neural interfaces being used for nerve repair. Two interfaces are used to reroute misdirected neural signals. The original signals are blocked between the two interfaces.

In order to learn the proper mapping from *input* microelectrode to *output* microelectrode, the use of a "neural network" is proposed. The network must be bidirectional to accommodate both efferent and afferent signals. Furthermore, both the input and output of the network must correspond to

the firing rates of axons. The difficulty with this problem is that there is no way to gain access to a *desired* response for the output of the network as would be required to train a traditional neural network. There is only a desired response for the *hand* as a whole, not for individual axon signals. In order to overcome these problems, a new algorithm, based on a variety of neural network techniques has been developed which appears to solve the mapping problem for a one-to-one descrambling.

The problem of rerouting axons is analogous to the classical linear assignment problem. We wish to assign N input axons to N output axons (N people to N tasks). The assignment can be made based on a *cost matrix*, \mathbf{C} , whose coefficients, $c_{i,j}$, give the cost, or gain in performance, of assigning input axon i to the output j . As will be shown, \mathbf{C} corresponds to *learned* information, with the coefficients being somewhat analogous to the synaptic weights in a neural network. To formulate the assignment it is also necessary to define an *assignment matrix*, \mathbf{T} . The coefficient $t_{i,j} = 1$ if input axon i is actually assigned to output j , else $t_{i,j} = 0$. \mathbf{T} is a sparse matrix since there is a single 1 in each row and each column. An optimal assignment is made by minimizing the cost function

$$J(\mathbf{C}, \mathbf{T}) = \sum_{i=1}^N \sum_{j=1}^N c_{i,j} t_{i,j} \quad (1)$$

subject to the constraints

$$\sum_{i=1}^N t_{i,j} = 1 \quad (2)$$

$$\sum_{j=1}^N t_{i,j} = 1 \quad (3)$$

$$t_{i,j} \in \{0, 1\} \forall i, j \quad (4)$$

There are many classical linear programming algorithms to solve this problem. However, \mathbf{C} may also be used directly to determine the weights for a Hopfield network [18] which may then be used as an efficient method to find a "good" solution. What makes the assignment problem difficult is that we are never given the cost matrix. Initially there is no knowledge of how individual axons are to be assigned. This is similar to a case of the *traveling salesman* problem in which the distances between the cities, the \mathbf{C} matrix, is initially unknown. Only the **total** path length after a trial journey to the cities is known. From this, the salesman is expected to learn the best path. Learning is reflected in the proper formulation of a cost matrix.

First define the following parameters: Let \bar{E} be the average error in the hand's performance over the training period. Let E_k be the instantaneous error for a given volitional command. Then $\varepsilon_k = E_k - \bar{E}$ is a semi-quantitative measure of how well the hand performs for a given command relative to past performance. Basically, ε_k can be thought of as a subjective measure of how well the hand is currently performing. Also define x_i as the average impulse frequency or firing rate along input axon i during the course of the current command.

The rule for adapting the elements of the cost matrix can now be defined as follows:

$$(c_{i,j})_{k+1} = (c_{i,j})_k + (\Delta c_{i,j})_k \quad (5)$$

$$(\Delta c_{i,j})_k = \mu \varepsilon_k x_i t_{i,j} \quad (6)$$

The form of this learning algorithm is similar in nature to the LMS algorithm which is used in almost all neural networks. Individual cost coefficients are adapted in proportion to the strength

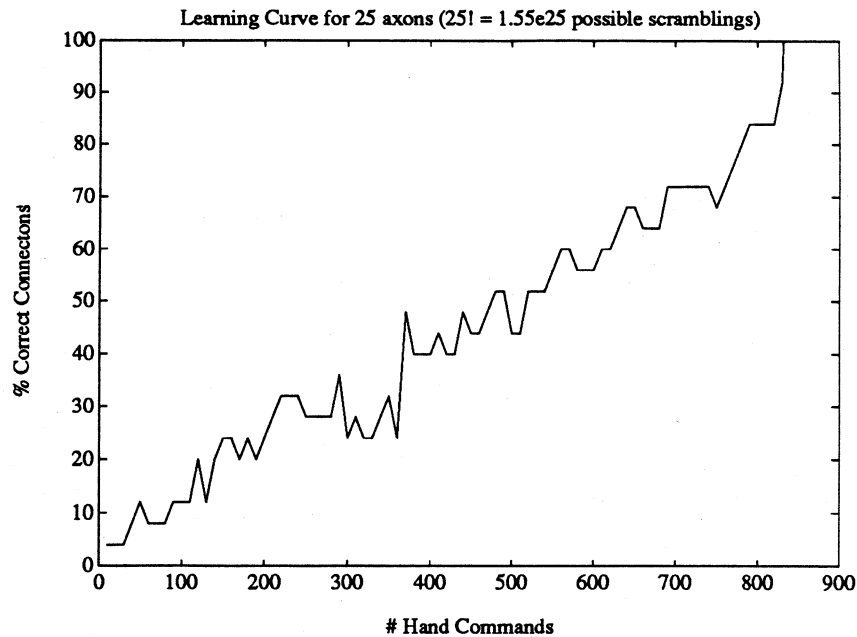


Figure 5: Learning curve for axon descrambling simulation.

of the input; the greater the input the greater its contribution to the total output error. Unlike LMS, which adapts each output neuron with respect to an individual error, all coefficient are changed in proportion to the total error. This is necessary since the desired output for each axon is unavailable. In summary, we adapt the individual cost coefficients associated with the current assignment in proportion to the total output error and the input strength at each axon. In this way, the cost matrix is adapted to reflect the overall performance of the current assignment. The complete sequence of training would proceed as follows:

1. Start with a random cost matrix.
2. Use a Hopfield Net to form an initial assignment matrix.
3. Based on the assignment matrix electronically reroute the axon signals.
4. Have the patient give his hand a command (i.e. make a fist).
5. Based on the error adapt the coefficients of the cost matrix.
6. Based on the new cost matrix use the Hopfield Net to find the new assignment matrix.
7. Go to step 3.

This procedure would continue until a suitable level of performance is achieved. This algorithm is intuitively motivated. A proof of convergence is unknown and possibly intractable considering the qualitative nature of the error used for adaptation. While it will be years before the algorithm can be fully tested on human patients, a learning curve for a computer simulation with 25 axons is shown in Figure 5. The simulation assumed a worst case situation in which all axon signals were taken to be uncorrelated. For 25 axons there are approximately 1.551×10^{25} possible reroutings. A complete descrambling was achieved in under 900 attempts.

4 Limb Prosthesis

In an amputation, rerouting neural activity as explained above will be of little use to the patient. In this case, the interfaces can be used to establish direct communication to a limb prosthesis (i.e. a mechanical hand) ².

Interfaces which could presently be applied chronically in a limb prosthesis application can not provide access to anything but gross averages of neural activity. Current techniques utilize mechanical command signals from unaffected tissues (e.g. shoulder movement) or electromyographic (EMG) signals from isometric contraction of muscles to control prosthesis movements. Problems commonly cited with respect to myoelectric prostheses include lack of reliability of the EMG electrodes (e.g. susceptibility to faulty operation in the presence of perspiration), the need to concentrate constantly on the muscles used to maintain a grip, and the lack of any shear (slippage) force feedback [19, 20]. As well, inconsistent placement of the electrodes can make the requisite signal processing extremely difficult [20]. In fact, old-fashioned, purely mechanical "claw" devices, which provide rudimentary proprioceptive feedback via their shoulder harnesses (Bowden cables), are preferred by many patients over more modern myoelectric prostheses [19]. The problems with these systems are all a result of limitations in the available interfaces between the patient and the prosthesis.

An ideal interface should allow for use of the limb via both the *normal* efferent (motor) and afferent (sensory) neural channels. Furthermore, since the ensemble behavior of the axons in peripheral nerves is what allows, for example, the fine motor control of the hand, it is clear that a successful interface must provide simultaneous access to the information carried in small groups or ultimately individual axons. All these requirements should be met with the current neural interface under development.

4.1 System Overview

The nature of the signals utilized by the peripheral nervous system to control various hand motions are both complicated and case specific. Thus, in order to utilize the thousands of signals available from the interfaces, it will be necessary to have an adaptive system capable of both utilizing the information content available in the signals and learning how the signals can be used to control an existing and fixed mechanical prosthesis. These requirements will be met through the use of artificial neural networks. Thus the majority of the burden involved in training will be placed on the prosthetic device themselves, rather than the patient.

A block diagram of a complete prosthesis system is shown in Figure 6, followed by an artist's conception of such a system shown in Figure 7. For *efferent* signals, following the neural interfaces and prior to the neural network, it would be necessary to perform some feature extraction to reduce the overall data rate of the system. This is performed in several stages. Initial feature extraction would consist of demodulating the neural signals from each microelectrode site on the neural interface into numerical representations of their effective axonal firing rates. Within the stump, these demodulated signals would be multiplexed into a common signal and then transmitted to the external prosthesis hardware via a telemetry system ³. Following this, an *adaptive* feature extractor would be utilized to cluster signals into functionally similar groups and then form an average demodulated signal for each feature signal. This additional data reduction is necessary to reduce the complexity of further processing. Finally, downstream from the feature extractor, an

²For the remainder of this discussion a "prosthesis" will refer to a full artificial limb prosthesis

³Suitable telemetry systems for bidirectional transmission of data in this application appear to be achievable with present technologies. For example, the simultaneous transmission of data and power via high-frequency electromagnetic coils has been demonstrated in prosthetic applications [10]

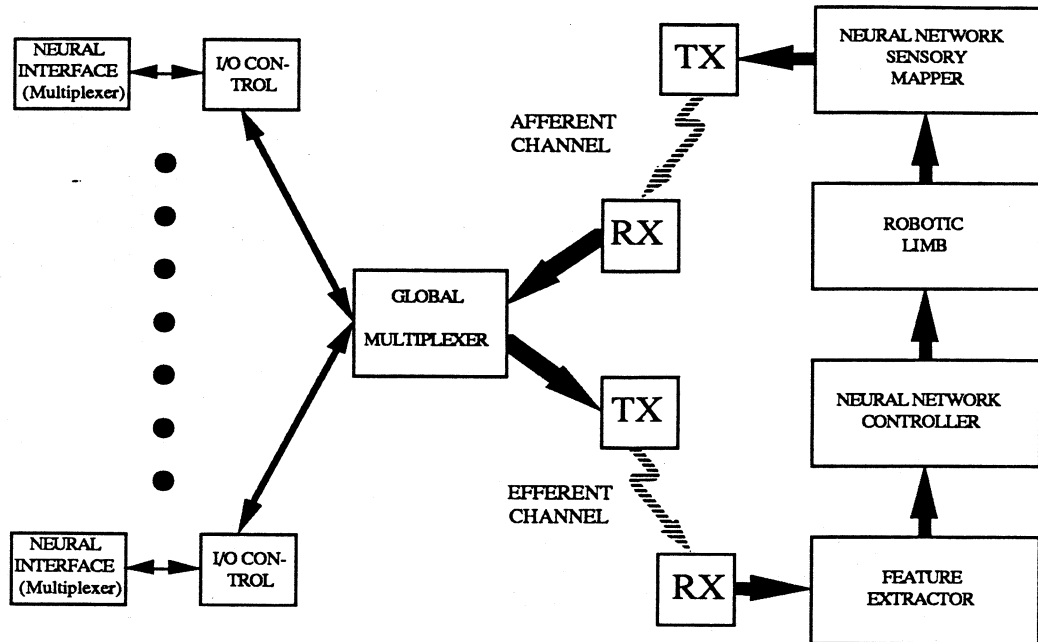


Figure 6: Block diagram of a directly interfaced prosthesis system. Signals to and from the neural interface for each fascicle are routed by I/O controllers which either demodulate or stimulate as appropriate for each microelectrode site. The data for each fascicle flows through a global multiplexer prior to the implanted transceiver. (Each transceiver is depicted as separate transmit (TX) and receive (RX) blocks.) Broken areas denote transcutaneous transmission of information. For the efferent channel, demodulated neural signals are processed by a feature extractor, followed by a neural network used to control the robotic limb. Information from transducers in the robotic limb is mapped onto the afferent channel by a neural network sensory mapper to provide feedback.

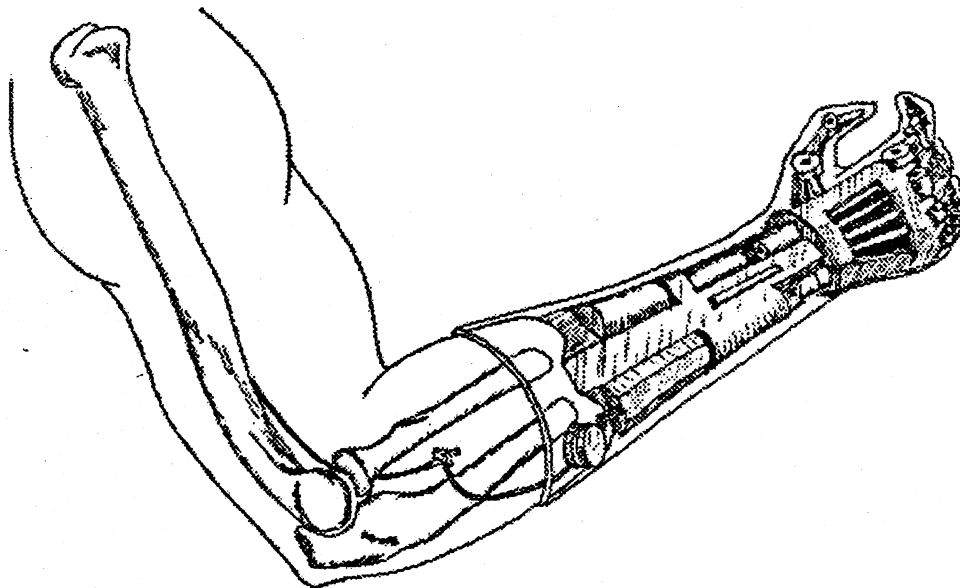


Figure 7: Artist's conception of a directly interfaced below-the-elbow limb prosthesis.

adaptive neural network in the prosthesis would carry out the interpretation of the neural command signals and the control of the mechanical systems of the prosthesis.

For afferent information, signals would be processed in a similar manner, but in a reverse direction. Signals from transducers in the prosthesis would be mapped onto the appropriate sensory channels using a second adaptive network. The outputs of the adaptive network would consist of numerical representations of the desired stimulation rates at the microelectrodes. Signals from this network would then be multiplexed into a common signal and transmitted into the stump. This information would be demultiplexed and routed to the appropriate microelectrode sites to determine their stimulation rates.

4.2 Training Methodology

The following technique could be used to establish a basic set of neural command patterns with which to train the *control* of the prosthesis and to simultaneously sort axons into afferent or efferent groups. The patient would be asked to mimic, with his or her "phantom" hand, a predefined set of motions which could be presented using a computer-generated representation of a hand. Several records of the neural firing patterns (demodulated as explained below) corresponding to each motion would be stored for later use in "off-line" training of the feature extractor and neural network control system. It may also be useful to have the patient carry out a set of hand motions with a normal hand (if present) using a device such as the "data glove" ⁴ to directly measure the joint angles and positions in the state space of the hand. This would allow some of the motions to be defined by the patient to better suit his or her individual needs. In order to separate afferent from efferent axons, the axonal signals which showed no consistent electrical activity during these tests would be classified as afferent. The individual microelectrode sites corresponding to them could then be defined as sites for stimulation if the prosthesis is to be equipped with sensory input transducers. The process for incorporating sensory capability in the prosthesis will require a separate procedure. While the characteristics of the transducers on the prosthesis itself will be known, sorting out the different classes of afferent fibers (tactile sense, proprioception, pain and temperature sense) is likely to be a much more arduous task. The major difficulty would be that the user, when presented with various stimuli would somehow have to report his or her perceptions to the sorting algorithm. A proposed method for training sensory information into the prosthesis which also utilizes a neural network will be presented in a later section.

5 Feature Extraction

5.1 Initial Data Reduction: Demodulation

Since the information contained in the peripheral nervous system is encoded using pulse-frequency modulation and recruitment ⁵, only the presence and rate of occurrence of individual action potentials would need be detected in efferent signals. Axon firing rates for normal levels of excitation fall within the range of 5 - 100 action potentials per second [26] with a conservative upper limit of 500 Hz. If each microelectrode site was equipped with a simple circuit for registering the occurrence of an action potential signal (threshold detection) between sampling intervals, it could be assumed that scanning the array at 500 Hz would provide all of the necessary information. This is in contrast to the sampled recording of action potential waveforms, which have frequency components extending out to approximately 10 KHz and hence require a higher sampling rate.

⁴The data glove is a device worn on the human hand and is used for measuring joint angles [25].

⁵Recruitment refers to increasing the number of active motor units.

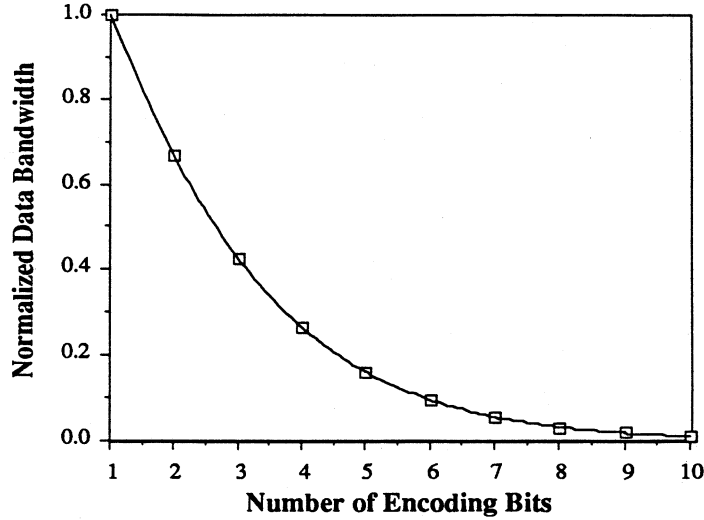


Figure 8: Graph showing the decrease in net data bandwidth with increasing number of encoding bits used to store the frequency of action potentials at a given microelectrode site.

In considering efferent data reduction, one can observe that the action potential frequency may be relatively high for each axon, while the rate of change of this frequency with changing commands for desired motions will generally be much lower. These commands (*symbols*) have a low data rate due to the relatively long mechanical time constants of the musculoskeletal system.⁶ If one attempts to perform a repetitive simple hand motion, such as tapping the index finger against a tabletop as rapidly as possible, the maximum rate is a few Hertz. Thus the number of action potentials over a given sampling interval could be converted to a numerical or demodulated representation of the average firing rate without undue loss of information. The output data rate for each microelectrode site would then be the product of the number of data bits used to specify the firing rate and the reciprocal of the sampling interval. Mathematically, this is expressed as,

$$DR_{demod} = N \left(\frac{DR_{raw}}{2^N - 1} \right) \quad (7)$$

where DR_{demod} is the demodulated data rate, N is the number of bits used to specify the firing rate of the demodulated signals, and DR_{raw} is the raw data rate. A plot of this function is shown in Figure 8. The cost of adding encoding bits is both one of increased power dissipation and of increased real estate usage on the integrated circuit. The benefit in terms of reduced bandwidth is clear.

In order to estimate the total efferent bandwidth for the system, one first needs to consider the total number of axonal signal sources. Referring to the intraneural (fascicle) maps of Sunderland [22, 23]. it can be seen that the radial nerve is divided into 8-10 fascicles near the elbow. The ulnar nerve is divided into approximately 13 fascicles, and the median nerve into approximately 14, at this level. Thus roughly forty monofascicular neural interfaces would be required, for a total of 40,000 microelectrode signals. Assuming that half of these are efferent, with each site being sampled at 500 Hz, and a 5-bit symbol sample rate of 16 Hz, the system data rate would be only 1.6 Mbits/s (versus the raw signal data rate of 10.2 Mbit/s). For a slower-responding prosthesis

⁶And perhaps by bandwidth limits of the cerebrum and cerebellum which evolved concurrently and presumably without needless excess speed.

with an 8-bit encoding and a 2 Hz symbol sample rate, the system data rate would be only 320 Kbits/s (roughly a 60-fold reduction).

The demodulation of the action potential stream, from each microelectrode site, into its respective numerical signal strength could be accomplished by several methods. One such method would use what amounts to frequency counters for each axon. Either digital counters or analog charge-integrators could be utilized for this purpose. The digital counters would simply count action potentials over a given sampling period (each would require a comparator or the multiplexed output of a shared fast comparator for its clock). Each counter would be interrogated and then reset for the next sampling period. Another method, suggested by Franz [19], consists of the sequential storage of bits corresponding to the individual action potentials as time sequences for each microelectrode site⁷. Encoding logic could quickly scan the time histories for each site and output the desired numerically encoded rate value.

In a two-way neural interface, afferent information would be conveyed to the PNS as low-data-rate commands to stimulation circuitry located in the neural interface. This information would be encoded by a sensory mapper which would map signals from transducers in the prosthesis into pulse-frequency modulated signals for stimulation.

To minimize the problem of power dissipation into the neural tissue, the inclusion of the demodulation and telemetry functions in the circuitry of the neural interfaces would be avoided. The demodulators would be implemented in separate, synchronized companion chips, located in less thermally sensitive areas. The outputs from the microelectrode sites' demodulators would be scanned sequentially at the appropriate sampling intervals and routed to the telemetry circuits. Relatively high-power circuits could be located in such areas as alongside blood vessels or attached to bone. The implanted telemetry circuits could also be affixed to bone in order to facilitate heat dissipation if necessary.

5.2 Efferent Signal Clustering

In the normal neuromuscular system, thousands of functionally similar axons innervate a single group of muscle fibers to regulate its overall contraction. While individual signals could be applied directly as input to the neural network, this would be an unnecessary complication. From an engineering standpoint, we are interested only in the total muscular force level. It should thus be possible to perform massive data reduction by clustering the individual microelectrode site signals into functionally similar groups. The average firing rate within each cluster can then be used as a single representative signal for that cluster. The average of the demodulated signals from each cluster will henceforth be referred to as a *feature extracted* signal.

Ideally we would want only one feature extracted signal corresponding to each muscle in the hand. However, it will probably be necessary to have several feature extracted signals for each muscle to account for such factors as motor neuron size and recruitment order. This corresponds to simply grouping the individual axons into finer clusters. The number of necessary feature extracted signals will ultimately be determined by both the physiology of the human hand and the dexterity capabilities of the prosthesis mechanism to be used. This data reduction subsystem is shown in Figure 6 in relation to the overall prosthetic system. It is estimated that this subsystem will enable a reduction in data by roughly two orders of magnitude.

The time histories of the axon firing rates, recorded from the patient as previously described,

⁷The memory required per neural interface, based on the above estimates, is less than that of the now obsolete 64 K-bit dynamic RAM memory. Thus, for all forty fascicles a 2 M-bit RAM would be sufficient. (For 1,024 sites per neural interface and a 10 Hz sampling rate of the microelectrode time sequences, 64 storage locations per site would be adequate with a 500 Hz maximum action potential rate.)

will comprise a set of training vectors for the clustering algorithm. The dimension of the input vectors is extremely large corresponding to the sampling period and interval over which the time histories are recorded. The number of signals corresponds to the number of efferent microelectrode sites. The goal is to cluster the sites into groups which are highly correlated. This clustering can be performed in many ways, using a traditional approach such as the Linde-Buzo-Gray (LBG) algorithm [27] used in vector quantization, or a neural network approach such as Kohonen's self organizing feature maps [28].

After training, the microelectrode signals will be clustered into groups which have similar time histories. Thus the axons should be functionally grouped according to the various muscles that they originally controlled. It is important to note that the adaptive process by which the clusters are determined is performed only once and off-line, using a computer. Once the appropriate cluster for each axon site is identified, the information is used to program the actual feature extraction subsystem. The programmed subsystem merely needs to average the firing rates from each axon site within each known cluster during normal operation. This average firing rate for the cluster forms the feature extracted signal which can then be used as input to the next stage of the prosthetic system, the neural network.

A possible hardware implementation for the feature extractor would entail the use of digital logic to compute the feature extracted signals. Each microelectrode site would be assigned a numerical mapping address corresponding to the cluster into which it had been classified. As the demodulated outputs from the microelectrode arrays are scanned by the feature extractor circuitry, the mapping addresses could act as pointers to summing registers into which each demodulated output would be added. These *cluster sums*, normalized by the number of microelectrode signals within each cluster, would represent the feature extracted signals at the end of each scan through the array. With such an implementation, the off-line adaptation of the feature extractor would merely produce a look-up-table of mapping addresses. These mapping addresses could then be downloaded into a non-volatile memory structure within the feature extractor to enable its operation.

More sophisticated feature extraction methods have also been considered but appear to be impractical. In EMG analysis, for example, signals are often modeled as ARMA (auto-regressive moving-average) processes [29]. One then uses a Bayesian classifier based on the parameters of the ARMA model to map neural commands onto a limited number of control sequences. Unfortunately this method is usually limited to on/off control with the intensity (force or velocity) being regulated by signal power. Also, extracting the ARMA parameters cannot be done on-line. A short time window of data must be stored and then processed. This results in unavoidable time delays. Furthermore, an EMG measures muscular activity which is based on an ensemble of neural activity. It is thus naturally amenable to stochastic analysis. Since we are working at a higher resolution than EMG signals, we would require a more sophisticated stochastic model for feature extraction. However, stochastic models are not a feasible option when considering the number of microelectrode sites involved. In addition, they do nothing to reduce the total number of distinct signals in the system.

6 Efferent Neural Network Interface

In the prosthetic system, the neural network would act as the bridge between the neural signals and the actual robotic hand. It can be considered as the *intelligent* interface between man and machine. Its function is to interpret the microelectrode signals and drive the robotic hand so as to make the use of the prosthesis transparent to the patient. To the patient, controlling the prosthesis should seem the same as controlling the original hand.

The training of the neural network will be done completely off-line using computer models of

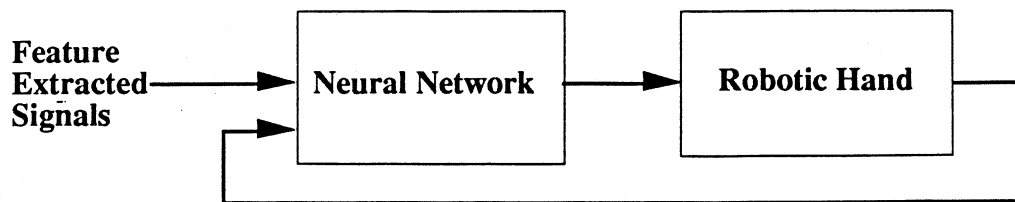


Figure 9: Block diagram of a proposed neural network based prosthesis controller.

the neural network and signal recordings made while the patient mimics desired hand movements. The patient's hand motions are sensed using a data glove whose outputs are used to form a desired response for the neural network. Once the neural network computer model is trained, the values of the synaptic weights can be downloaded to the actual neural network hardware. The customization of the prosthetic system for the individual patient should then be complete. However, additional training cycles may be necessary to emphasize certain motions to achieve fine motor control.

Prior to describing in detail the design of the neural network, it is necessary to briefly discuss how the CNS uses axons to control a limb. Simplistically, agonist and antagonist muscle contractions determine tendon tensions resulting in joint torques which ultimately determine limb position. Muscular activity is, of course, directly related to neural activity. The multiple axons associated with a single muscle regulate its contraction. A muscle is typically modeled as a simple second order dynamic system. A static hand and arm position corresponds to an *equilibrium point* in both neural and muscular activity. During the course of a movement the CNS specifies a *virtual trajectory* [30]. A point along the virtual trajectory corresponds to what the limb position would be, given that the current neural activity specifies an equilibrium point. The virtual and true trajectories are related through the inherent inertial and viscoelastic properties of the limb and muscles. (In other words, the virtual trajectory is the control input to a dynamic system, the output of which is the actual trajectory.) The underlying principle which dictates the necessary virtual trajectory control is believed to be a simple smoothness constraint on the limb trajectory [30].

It is thus clear what the neural network must accomplish. The network is provided with a set of neural recordings (the feature extracted signals) which contain information about the virtual trajectory, and the corresponding desired true trajectory (taken from data glove measurements). In order to control the robotic hand, the neural network must be capable of extracting and internally learning the original hand dynamics. In addition, it must be capable of compensating for the fixed dynamics of the robotic hand as it learns the proper control of the prosthesis. With the above in mind, we now propose two methods of implementing the neural control system.

6.1 Neural Control System

The first system shown in Figure 9 is attractive in its simplicity. A single feedforward layered neural network is used to both interpret the feature extracted signals and drive the robotic hand (RH). The output of the neural network corresponds to input levels for the various actuators which directly control torques or tensions in the mechanical hand. Training can be accomplished using a variation of the *backpropagation through time* algorithm [31]. This is a non-linear control

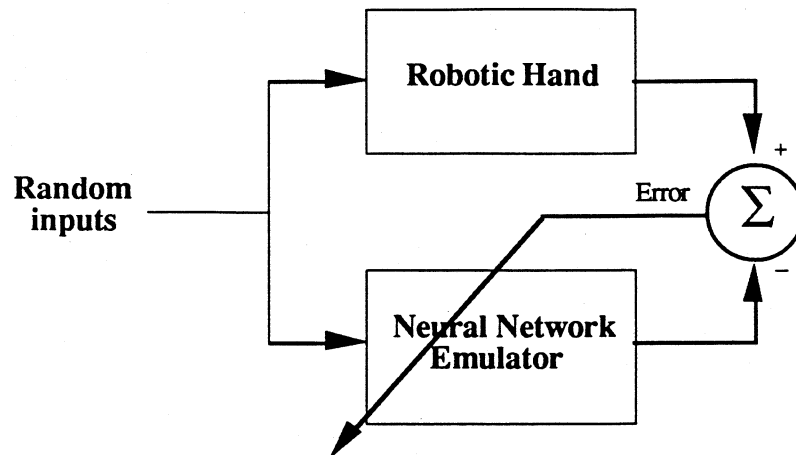


Figure 10: Block diagram of a neural network as configured for non-linear system identification to form an emulator for the robotic hand.

problem similar to the *Truck-Backer-Upper* problem⁸ with some important differences. First of all, the inputs to the system are not simple command step functions, but complicated neural inputs which contain virtual trajectory information. In fact, it is somewhat misleading to think of the neural network as a controller. The CNS is the actual controller. The neural network is more of a dynamic precompensator to the mechanical system which insures the CNS control signals are properly interpreted. Furthermore, during training a desired response is available throughout the entire trajectory. This is in contrast to many control problems which only specify an end point. Thus, to properly adapt the network, it is necessary to use both the instantaneous trajectory error and prior gradients accumulated while backpropagating through the system from previous time steps.

This training algorithm also requires a model of the robotic hand. This is necessary since the known desired response occurs at the output of the mechanical hand and not at the output of the neural network. In order to formulate the appropriate desired response for the output of the network, one needs the *Jacobian transformation* which relates small changes in the neural network output to small changes in the mechanical hand output.

In general, detailed modeling (e.g. coriolis, centrifugal, and mass matrix terms) for existing robotic systems are not readily available. As an alternative, one can form a neural network emulator of the RH. Using a neural network in a non-linear system identification mode is illustrated in Figure 10. One can then use backpropagation through the emulator to form the necessary desired response for the neural network.

6.2 Neural Interpreter System

As an alternative to the above approach, which requires the modeling of the RH, a second system is proposed which involves decoupling of the interpretation of axon signals from the low level control of the RH (see Figure 11). This allows one design of the neural network *interpreter* virtually independent of all robotic hand modeling considerations.

Existing robotic hands normally utilize low level control systems (LLCS). The LLCS for the Utah/MIT Hand [33] includes 16 variable-loop-gain position servos to operate the finger joints

⁸The *Truck-Backer-Upper* problem is a non-linear control problem in which a neural network is trained to back a truck up to a loading dock [32].

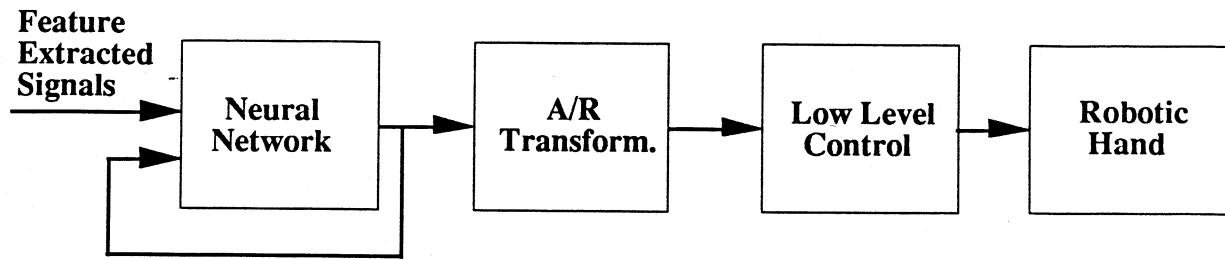


Figure 11: Block diagram of the multi-level scheme for the neural network prosthesis controller.

and 32 variable-loop-gain tension servos. For example, as input to the LLCS one can specify independently a specific joint angle. The LLCS is designed to insure that the desired angle is achieved.

Achieving higher level control of the RH using a LLCS can be accomplished via teleoperation (i.e. a human operator using a data glove). A simple linear transformation can be used to map anthropomorphic joint angles from the data glove to robotic joint angles for input to the LLCS. This transformation (referred to as the *anthropomorphic/robotic* or A/R transformation) is easily found by performing a least-squares fit over a predefined set of anthropomorphic hand poses with the desired robotic hand poses⁹ [34].

Returning to the prosthetic system of Figure 11, it would now be necessary for the neural network to act only as an interpreter whose outputs correspond to the joint states of the anthropomorphic hand. Since the desired hand states that must be recorded for training the prosthesis may be taken directly from a data glove, there is now a one-to-one correspondence between the measurements taken and the desired output of the neural network. The neural network can then be adapted using backpropagation without the need for a model of the RH to be controlled. Note, backpropagation through time is still required due to the state feedback from the output of the neural network. Once trained, the output of the neural network feeds into the A/R transformation which produces inputs for the LLCS that ultimately drives the RH.

Thus it would be possible to initially train the prosthetic system without any need for an actual robotic hand and/or model. It is important to note, however, that the neural network must be trained on trajectory information so as to be able to extract the original hand dynamics. If one merely trains static mappings from neural activity into desired joint angles then one is in essence training the network to learn equilibrium points. In this case, during actual trajectory formation, the network's output will correspond to the virtual trajectory rather than the actual desired trajectory. This could, in fact, be desirable if the composite LLCS and RH dynamic system could be made to correspond to actual human hand dynamics. In this case the virtual neural trajectory formed by the CNS would be transformed into a virtual joint trajectory by the neural network which would then be transformed into the actual trajectory by the LLCS and RH. Unfortunately, it would be incorrect to assume that the mechanical prosthesis could be designed to match the dynamic properties of a human limb.

Initially, it is more reasonable to assume that the dynamics of the LLCS and RH are fast enough

⁹A transformation which includes both joint angle and joint stiffness will probably be desirable. This will require further research in order to implement.

to be ignored. In this case, without appreciable mechanical time constants, the neural network output must be made to correspond to the actual trajectory. This resulting inability to adaptively specify the overall dynamic characteristics, including robotic dynamics, is a minor drawback to this scheme. The patient's own ability to compensate for a "mismatch" in dynamics will need to be studied. However, it is evident that a person can easily compensate for fluctuations in dynamics in the natural hand as demonstrated by the ease with which we can manipulate objects.

It may appear from Figure 11 that control of the prosthesis is essentially being performed in an open loop fashion. Feedback does occur, however, both visually and through the afferent pathways. Even in the natural hand no feedback occurs internal to the hand itself.

7 Afferent Neural Network Sensory Mapper

The mapping of signals from transducers in the prosthesis onto the afferent neural channels would be controlled by a neural network based sensory mapper. The prosthesis could readily be equipped with transducers for tactile sensation, force, joint angle, temperature, and other sensory modalities. Utilizing such transducers would require the assignment of their output signals to neural pathways of the appropriate sensory modalities and perceived locations on the prosthesis.

The input to the neural network corresponds to the transducer outputs whose characteristics will be known. Forming the *desired response* for the network, however, will require the knowledge of the sensory modality with which each afferent microelectrode site is associated. The process of sorting out the various sensory modalities will likely prove to be a more difficult task than the utilization of the efferent information. Fortunately, the biological organization of the PNS is such that the fascicles are somewhat distinct in terms of dermatomes, muscles, tendons and joints innervated. Utilizing fascicle function maps such as those of Sunderland [22, 23] and Jabaley, et al [24], the fascicles could at least be tentatively identified and this information utilized to speed their initial classifications (or to coordinate the global functions of simple prostheses) using techniques described below. Thus the gross somatotopic location of each neural interface would likely be known as the nerve and perhaps the fascicle into which each interface were implanted would be known at the time of surgery. A proposed method for determining the modality and perceived location of each afferent microelectrode site involves a process of systematic stimulation as outlined below.

Initially the perceived locations of the entire group of afferent sites on each neural interface would be verified by their stimulation *en masse*. The patient would report the location at which the sensation appears. At this point, low-resolution areas of perceived sensation, or *fascicular dermatomes*, would be known and may well prove adequate for initial prostheses. The subdivision of each fascicular dermatome into higher-resolution regions and perhaps distinct sensory modalities could subsequently be attempted.

Stimulation of small groups of microelectrode sites, in numbers chosen such that they are at or slightly above the perceptual threshold, should allow the patient to indicate more precisely the locations of the perceived stimuli. While it is presently unknown if distinct modalities could be resolved in this fashion, future experimentation will undoubtedly yield a better understanding of how this could be accomplished. Currently one can only speculate about what the patient would actually perceive under stimulation. The only reports of such work known at this time [35, 36], indicate that only "tingling sensations" were described under gross stimulation of nerves.

Regardless of the ultimate resolution at which stimuli could be delivered to the patient, a neural network sensory mapper would be required to correctly distribute signals from the transducers on the prosthesis to the neural interfaces. The neural network inputs would be the transducer signals and the outputs would be numerical values representing the stimulus intensity required at each microelectrode site. These numerical outputs would be transmitted transcutaneously, as shown

in Figure 6, and converted to pulse-frequency modulated streams of stimulus current pulses by implanted circuitry.

In order to train the neural network sensory mapper, one could use the stimulation intensities at each microelectrode site associated with perceived sensory locations and modalities (determined as described above) for the training set of desired outputs. The corresponding inputs would be derived from the known characteristics of the transducers used. Given this training set, the feed-forward neural network could be trained to form an appropriate mapping from transducers to the microelectrode sites. Initial training could be done off-line, with fine tuning carried out with the interaction of the patient.

8 Additional Applications for Neural Network Interfaces

Additional uses for the neural interfaces and processing circuitry would be abundant. Once the prosthesis interface is established, the processing circuitry could be trained for alternative devices which could be connected to the patient. Thus the neural interface and associated circuits would constitute an extremely versatile man/machine interface.

Control of mechanical devices could be accomplished without the mechanical lag of the hand. For example, the control surfaces of an aircraft could be directly mapped to hand motions. Sensory ranges could be compressed or expanded to suit many applications. Microscopic manipulations, such as those of microsurgery, could be mapped into perceived macroscopic motions. New sense modalities could also be introduced. For example, radiation could be sensed using the appropriate transducers and mapped into temperature sensations. It should be noted that since information is bidirectionally transmitted into and out of the neural interfaces in a form suitable for telemetry, remote operation would also be inherently possible in these and other applications.

In addition, these devices will allow for a great deal of basic science research which should answer fundamental questions regarding the nature of neural information conveyed by the PNS.

9 Conclusion

This article has presented an overview of the neural interface technology under development by this group. Also presented was the use of such interfaces in nerve repair as well as proposed implementations for direct neural network interfaced hand prostheses. Naturally, other types of limb prostheses could eventually be realized using similar approaches. In order to achieve the goal of realistic and cost-effective devices, an active effort is being made to avoid the use of expensive and esoteric materials and fabrication processes.

The effort to realize such a prosthesis is a long-term, multidisciplinary project. It is expected that it will be on the order of a decade before clinically useful devices can be produced. In the meantime, it is hoped that some of the technologies developed in the course of the overall project will find uses in rehabilitation and basic science research.

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