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Single Site Myoelectric Control of a Complex Robot Hand

by

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Myoelectric control methods have been used in commercial prosthetic hands for about twenty years. Lower arm muscle action results in the generation of electric potentials which may be detected at the skin surface. Commercial prosthetic hands use these potentials to activate a binary control action: hand open/hand closed. There is no control over the force exerted by the hand. This is set at some 'average' value thought to be most appropriate for a wide range of circumstances. Consequently available commercial hand are of only limited practical use. This paper describes an improved myolectric control system capable of controlling a multiple degree of freedom (DOF) robotic hand. Spectral analysis of a single site myolectric signal is combined with a neural network to provide up to seven control signals. Tests on a range of volunteers have validated the robustness of the system. As a man-machine interface (MMI) the method is shown to have many potential applications including a novel means of robot programming and as an intuitive interface to VR environments.

Keywords: Myoelectric; robot; prosthetic; control

1. Introduction

It is common for lower arm amputees to retain the muscle structure of the lower arm, Fig 1. Commercial prosthetic hands detect the electrical activity generated by the action of these muscles and use the signal to control the operation of the hand (Radix et al, 1996). The control system consists of a pair of electrodes attached to the skin surface above both the flexor and extensor muscles just below the elbow. Stump muscle action results in the generation of electric potentials, the magnitude of which is detected by surface electrodes and used to control the opening and closing of the prosthetic hand. When a detected signal exceeds a specified threshold value the hand will open. Closing the hand requires the signal from the second electrode to exceed the specified 'close threshold'. Variations on this simple two-site-two-state' control method have been developed but are not commonly used (Roberts et al. 1995). Existing NHS prosthetic hands are therefore severely limited in their ability to emulate the behaviour of a real hand. Only a single DOF pincher movement is available. It is widely accepted that any improvement in the design of prosthetic hands is dependent upon advances in myoelectric control methods.

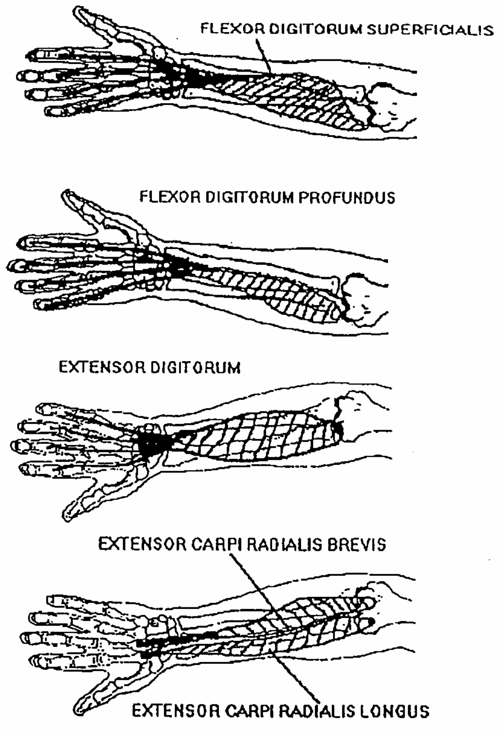

Figure1. Lower arm muscles contributing to ring finger motion.

Fundamental to the success of myoelectric control is the ability to reliably detect specified muscle actions, i.e. hand movements in an able bodied person and the equivalent muscle action in an amputee, in the presence of noise. Each hand movement is the result of a

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complex combination of muscle actions. To complicate matters further each individual produces slightly different muscles actions for the same hand movement. The electrical signal received at the upper arm surface electrode is a combination of time varying signals generated by several muscles. In order to reach the electrode these signals have propagated through different thickness' of tissue proportional to the distance between the electrode and the relevant muscle. Thus the received signal is a combination of time varying potentials, generated by a number of muscle actions, which have been attenuated and filtered according to their distance from the pick-up electrode. In addition the variables governing this process, e.g. thickness and quantity of arm bone and tissue, are different for each individual. It follows that any control system based upon the MEG (myoelectrogram) must be capable of discriminating between a wide variety of signals generated by similar muscle actions.

2. Experimental Procedure

A single pair of electrodes, situated about 1cm apart are attached below the elbow to the upper forearm of a range of able bodied volunteers. In addition a reference electrode is securely attached to the upper-arm using proprietary tape. Motion artefact, a serious source of signal degradation, is reduced to a minimum by ensuring a good contact surface between skin and electrode. Consideration of a range of electrodes resulted in the choice of Liberty Mutual MYO115 EMG research electrodes. Pick-up from the two electrodes is fed to a variable gain differential amplifier. The MYO115 includes on-board filtering giving a claimed 3dB response of 90-500Hz and a gain which may be customer specified between approximately 500 to 6000. Differential myoelectric signals of interest typically have magnitudes from a few microvolts up to a few millivolts. Without the filter these signals would tend to be swamped by induced 50 Hz noise created by nearby mains electrical equipment.

The amplified, differential myoelectric signal is fed to a PC using a PCl718 Advancetech PC interface card. The signals, sampled at a rate of 1 kHz, are captured from the arm surface in one second bursts, i.e. 1000 samples. A normalisation process ensures an RMS value of 1 volt. The resulting signal is applied to six filters operating within the range 0 Hz to 300 Hz, viz. <50Hz, 50-99 Hz, 100-149 Hz, 150-199 Hz, 200-249 Hz, and >250 Hz. Initial experiments used the LABTEC notebook and DaDisp signal processing package to examine the raw data. Subsequently a dedicated software package was developed which produced the filtering operations described above and calculated the RMS value of each filter output. This RMS value provides a measure of the power spectrum within each frequency band. Filters one and two, i.e. <99 Hz, are clearly operating below the low frequency -3dB level of the MYO115 electrode. Notwithstanding this unusual 'double-filtering' procedure results obtained from the <100 Hz frequency band were found to be crucial in identifying specific hand movements. The myoelectric signals associated with many specific hand movements have a significant low frequency, i.e. <100 Hz, content. The double filtering effect may therefore be regarded as a crude form of spectrum averaging.

The Nassi Schneidermann chart of Figure 2 illustrates the complete process. A neural net is fed the RMS values of the six filter outputs and trained to recognise specific patterns. Outputs from the neural network are then associated with specified hand movements. These positions are actioned in software by a complex, virtual hand and the result exhibited on a PC screen.

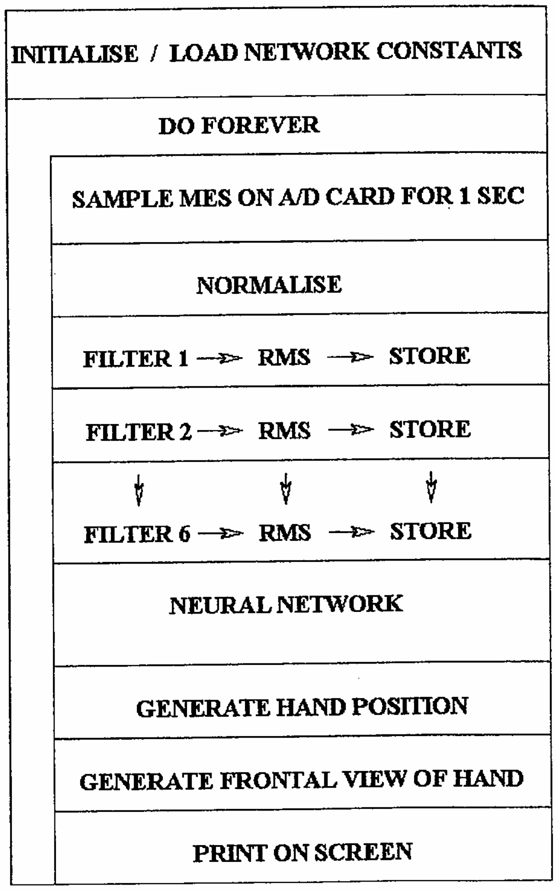


Figure 2 The Nassi Schneidermann Chart

A large number of experiments were performed in order to discover those hand/finger/wrist movements which could be most readily, and reliably, identified. Initial methods used the natural 'neural network' of the human brain. Two approaches were followed. In the first instance a spectrum analyser displayed the captured myoelectric signals in real time. Observations seemed to show some correlation between specific hand/finger/wrist movements and the resulting spectra. These results were confirmed when the differential myoelectric signals produced by the hand movements were amplified and played through a loud speaker. After a short learning period it was discovered that specific hand/wrist/finger movements could be clearly identified by their audio signal. It was this discovery which convinced the authors that a simple neural network should be capable of being trained to identify individual hand movements.

3. The Neural Network

Neural networks, with their ability to learn and recognise relationships between patterns of inputs, are ideally suited to recognising complex myolectric signals. In this case hand/finger/wrist movements are known to result from muscle actions, but the pattern between a complex combination of input muscle signals (detected at a single site) and output movements remains unclear. By feeding the prepared data, from the six filters, to a neural net, a transfer function and hence the causal relationship, can be learned. The neural net performs as an identifier of different input signals

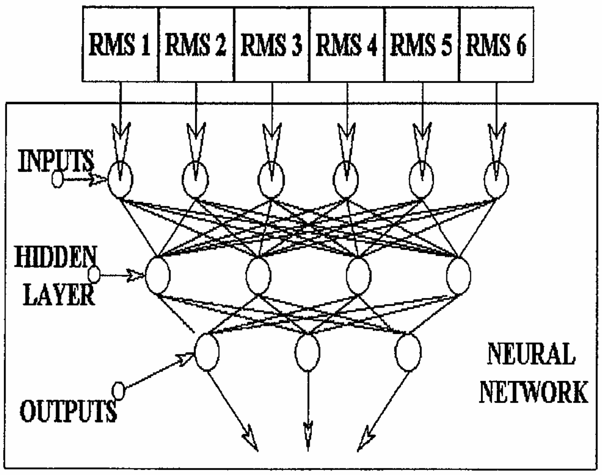


Figure 3 - The Neural Network

Empirical methods resulted in the choice of a back-propagation learning algorithm. This widely used algorithm learns from errors and is a form of the gradient minimisation problem. A simple neural network, Figure 3, consisting of six inputs, a hidden layer of four neurons and three outputs, is used to identify the hand action.

The neural network provides three binary output signals providing a potential of seven control signals: the relaxed condition, i.e. 000, is not considered to be a control signal. Training was done using a modified backpropagation algorithm with added momentum. This momentum helps to prevent the neural net becoming trapped in local minima of the error surface (Lau, 1992)

The network was trained with four training sets, representing four different moves. Each move was repeated four times to allow for variations. Initial experiments used the three neurons of the output layer to action three, single movements of the virtual hand, viz. a logical one at output one drives the hand to a specified position and ditto for outputs two and three. Clearly, however, the control system is capable of executing seven movements, i.e. the binary output range of the neural network.

For simplicity, and to prove the technology, only one action at a time is identified. The output of each neuron in the output layer lies between 0 and 1 due to the implemented transfer function. The Sigmoid function, i.e. $y=1/[1+\exp(-x)]$ was used for all neurons to compute the firing threshold of the neuron.

4. Results

Myoelectric signal spectra obtained from movement of the ring finger, i.e. the third finger, is shown in Figure 4. Scans S1 to S4 illustrate the results for the same individual repeating the ring finger movement four times. Care is taken to try to ensure that each action is identical to the previous movement.

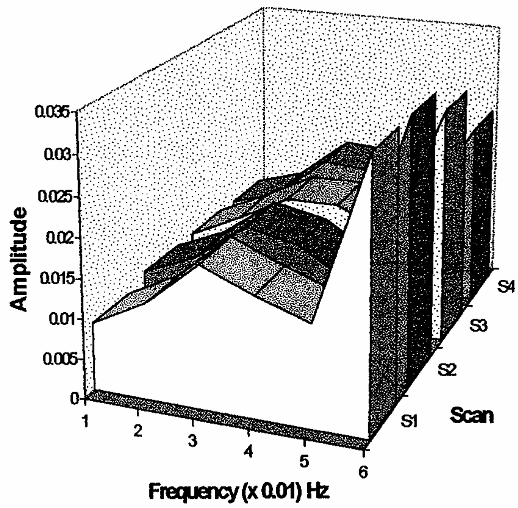


Figure 4 - Ring finger movements

In practice it is extremely difficult to ensure range of movement, speed of action and force applied remain constant. Differences between each set of experimental data are clearly visible. However the general 'shape' of the spectra resulting from this single finger movement remain fairly constant.

Figure 5 shows typical spectra from four specific positions of the hand/finger/wrist..

S1. Relaxed hand, i.e. fingers and thumb held out straight.

S2. The ring finger bent so that the tip touches the palm.

S3. Hand relaxed, wrist bent inwards towards the palm.

S4. Little finger bent inwards to touch the palm.

The results of Figure 5 were obtained from a single individual. Different people produce unique 'spectral identities' but the overall relative patterns, for similar movements/positions, remain fairly consistent.

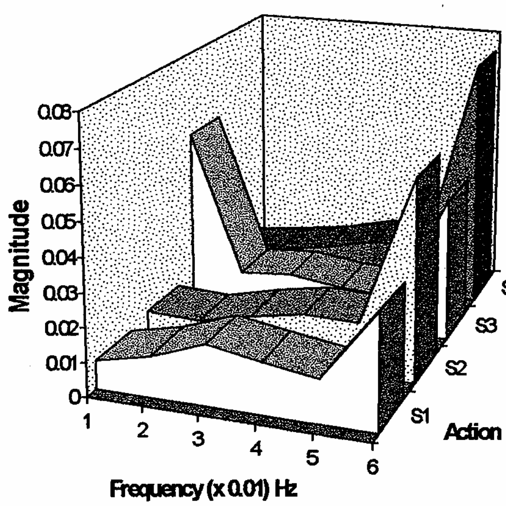
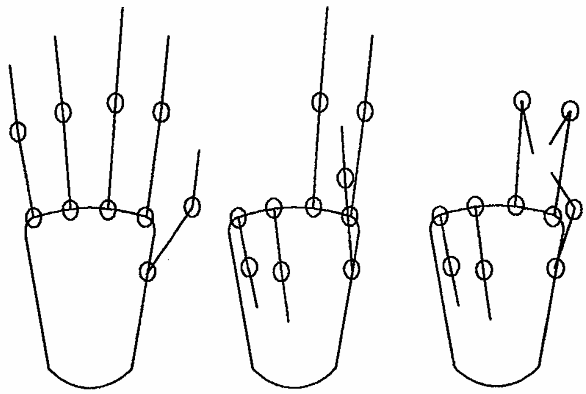


Figure 5 - Spectra from four hand positions

The above movements of the hand and/or wrist were identified by the neural network, and used to control the action of a virtual robot hand, Figure 6. In this case the three simple positions mentioned earlier are illustrated, i.e. the relaxed position and the two finger parallel and chuck grasps. These position were identified as being useful to a user of prosthetic hands. The positions adopted by the virtual hand do not necessarily replicate the position of the volunteers' control hand. The intention is not that the robot hand will exactly replicate the movements of the biological hand. The aim is for the user to be able to reliably control a complex prosthetic hand using simple muscle movements of the upper forearm.

From a practical viewpoint it is important that the exertion necessary for the muscle control does not become so excessive as to render the user exhausted after a short period of use. Simplicity of action is therefore of crucial practical importance. In this regard the amputee has one advantage over the able bodied person. In order to exert force the able bodied user must grasp an object or press the fingers against each other or



a. Hand relaxed b. Parallel grasp c. Chuck grasp

Figure 6. Useful hand positions

into the palm of the hand. Because of the way the forearm muscles are terminated in many amputees the ability of the muscles to emulate the action of varying force is retained. Crucially this ability is maintained without the need of an external opposing force. The magnitude of the myoelectric signal is proportional to the force exerted. The potential exists for this effect to d add a further dimension to the control system. It is intended in the near future that the magnitude the signal will be used to provide a greater combination of output signals and hence a more sophisticated control action.

5. Further Developments

The above results demonstrate that the frequency components of the MEG (myoelectrogram) signal from a single probe carry enough information to discriminate several hand positions. An advantage of the spectral approach is the robustness of the system against electrode efficacy fluctuations. Work towards a more refined analysis is pursued. For instance, at present, binary commands are extracted from the MEG, e.g. 'open hand', 'chuck grasp' etc. For a more natural operation of a prosthetic hand, it is necessary to also extract force information from the signal. It is well known that the magnitude of a MEG signal is proportional to the force applied. The authors believe that force information may also be encoded in the frequency spectrum of the signal. Success along these lines would lead to a force-sensitive system robust against fluctuations in probe efficacy.

At present, the signal is sampled during one second, its amplitude is normalised, its energy is computed in six

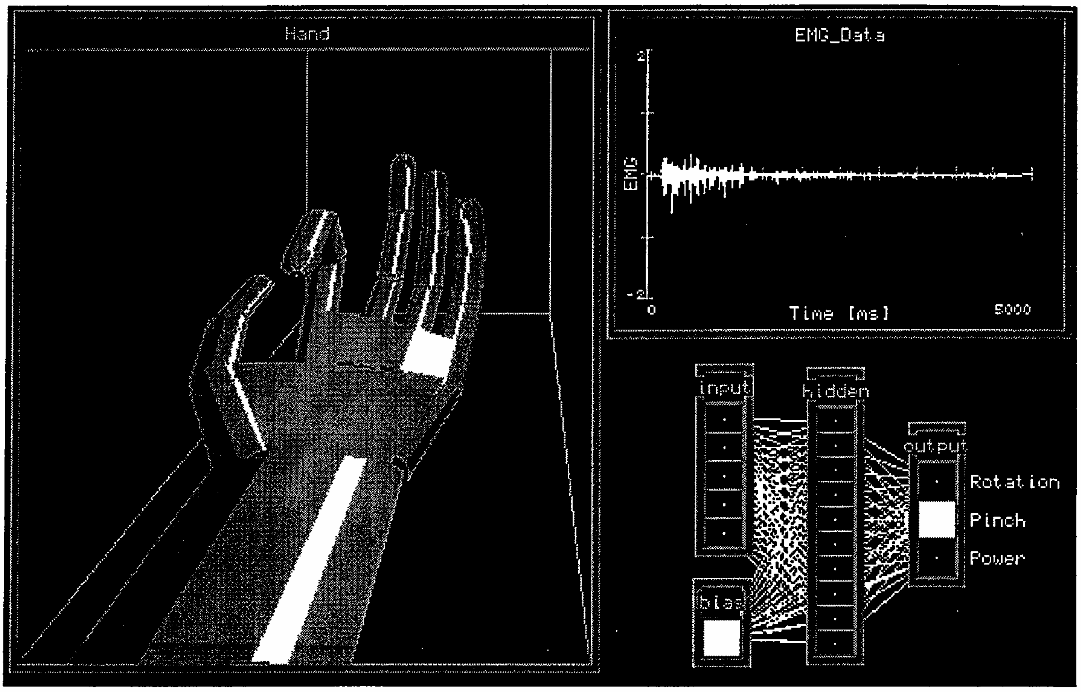


Figure 7 - Advanced virtual hand, associated EMG signal and neural network

frequency bands, then the results fed to the neural network which evaluates the hand position encoded by the signal. This procedure causes a relatively long reaction time. Shortening the reaction time to less than 100ms is desirable for a practical system. In order to achieve this objective, future developments are aimed at normalising the amplitude using hardware filters and a new low power analogue neural network chip developed at the University of Plymouth [Coue and Wilson, 1996a, 1996b].

Finally, the conception of a training procedure is to be investigated. To train the neural network it is necessary to know which intended movement corresponds to the recorded signals. One solution may involve a more complex virtual hand which adopts a sequence of positions, Figure 7, that the patient would be asked to copy with his (missing) hand. There is also the possibility that prosthetic users could chose which positions of the hand were of most interest. An office worker, for example, would be likely to chose a different set of actions to a manual worker. The neural network would then be trained to reproduce the movements of the virtual hand, using the signals recorded on the subject. Once the patient is satisfied that the neural network has learned to produce the correct movements, the neural net can be transferred onto the real prosthetic hand.

Figure 7, shows the system under development for training a neural network to reproduce the movements intended by the patient. The window to the left displays a moving virtual hand. The graph on the top right shows an example of a raw MEG signal recorded during the following sequence of positions: 1. Rest 2. Thumb / index finger in a pinched grip, 3. Thumb / index finger parted forcefully and finally 4. Rest. In the future is hoped that this system will operate in real time in response to the user lower arm muscle movements.

6. Conclusions

Myoelectric signals, obtained form a single site on the lower arm, are capable of controlling a complex robot hand. The robustness of the method has been successfully demonstrated using a number of able bodied volunteers. It was discovered that a trained neural network will often operate satisfactorily for a range of different individuals. The present system has been implemented using only four separate control actions. However seven separate actions will be implemented in the near future. It is also feasible to arrange for a 'library' of different hand movements to be stored and recalled by the user as and when required. Each of these libraries would contain a combination of up to seven specialised hand positions and/or force values.

Time delays experienced with the prototype system are unacceptable for practical applications. Implementation of dedicated analogue filters and neural networks, developed at the University of Plymouth, are expected to reduce these delays to approximately 100mS. This work is included in the next phase of the project.

Practical implementation of these control methods for disabled users is dependent upon the development of an improved NHS prosthetic hand. The ideal hand would be physically attractive, inexpensive, lightweight, include multiple finger joints and force control. A joint project with a major prosthetic manufacturer to construct such a hand is presently under evaluation. However it is unlikely that such a device will be available in the near future.

Other possible application areas, presently under investigation, include a novel method of industrial robot programming, robot teleoperation (NASA is evaluating myoelectric control methods for use with the shuttle robot arm) and as a biologically intuitive interface for VR environments. It is possible that in the near future myoelectric control will become an important MMI (man machine interface) technology enabling natural body actions to be used to control complex hardware and software systems.

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