Proc. 2002 Australasian Conference on Robotics and Automation
Auckland, 27-29 November 2002

Grasp Recognition From Myoelectric Signals

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Abstract

Current myoelectric prosthetic hands enable the user to enact a simple grasp with a strength proportional to the contraction of certain muscle groups. This paper discusses the development of a system that will allow complex grasp shapes to be identified based on natural muscle movement. The application of this system can be extended to a general device controller where input is obtained from forearm muscles, measured using unobtrusive surface electrodes. This system provides the advantage of being less fatiguing than traditional input devices. The instrumentation hardware, computer software and algorithms developed to achieve this task are described in this paper.

1 Introduction

Hand amputees at present have the option of several kinds of prosthetic device. Apart from cosmetic hands or mechanically activated grippers there is a range of electrically driven hands available. Many of these are activated by the user contracting a single muscle with the resulting electromyographic signal activating the opening or closing of a single degree of freedom device. The speed and strength of the grip may be proportional to the signal that is read. The work presented in this paper stems from the desire to create a more advanced prosthetic system. The anticipated use for the artificial hand is as a robotic anthropomorphic device with multiple degrees of freedom. Such a hand is being developed at the University of Canterbury, but there are many suitable devices being researched worldwide [Jacobsen *et al.*, 1986; Kyberd *et al.*, 1998]. To control these more complex hands requires a more advanced human-machine interface involving multiple EMG (electromyographic) electrodes and a suitable pattern recognition system to interpret the raw signal. Ideally this system would require the user to undergo minimal training and therefore the control inputs should be as natural as possible. Muscles in the forearm are responsible for the coarse grasp shape made by a human hand, while muscles intrinsic to the hand are responsible for the fine grip and movement. After a hand amputation many of the muscles in the forearm remain and can still be used by the amputee. EMG signals can be read from these and used as the control source for the prosthetic device.

The system can also be used by able-bodied individuals as a machine interface to replace traditional controllers such as joysticks. The advantage to this includes less fatigue and a more natural movement. A successful controller will need minimal training of the operator. Many studies have looked into controllers of this type with mixed results. Early work mostly involved simple, single channel signal identification. Hudgins *et al.*, [1993] first showed that the myoelectric signal exhibited a deterministic pattern during the early phases of muscle contraction. Researchers have used various methods for identifying limb motion based on EMG signals, including multilayer neural networks [Englehart *et al.*, 2001], Hidden Markov Models [Jorgensen *et al.*, 2000] and Fuzzy ARTMAP Networks [Vuskovic and Du, 2002].

Control of an artificial hand, whether a prosthetic device or a robot manipulator, is achieved by placement of a number of EMG electrodes at specific locations on the surface of the forearm. Each sensor measures the surface potential at two points, the potential difference being directly proportional to the amount of contraction of the underlying muscle. In the Canterbury system information from these sensors is sampled by a desktop PC via a USB interface. Custom software written in C++ is used to process this data in a Windows based environment. The algorithms used are designed to be portable for future use on a fast DSP when the entire system moves to a stand-alone arrangement.

The aim of the software is to recognize the basic grasp shape being enacted by the user, based solely on the EMG measurements.

2 System Description

The object of the work presented here is to have a self-contained device taking signals from EMG electrodes on the arm and providing control signals to a prosthetic hand.

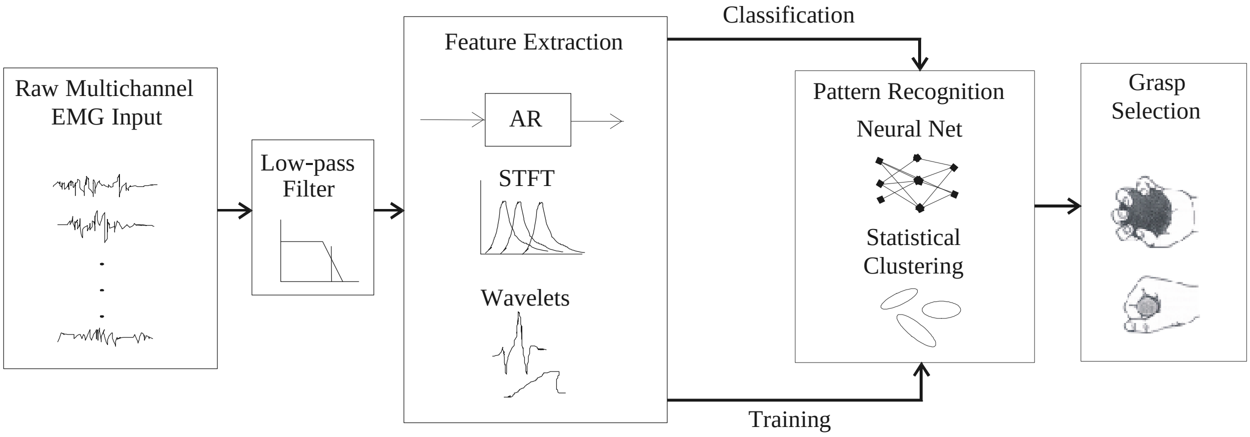

Figure 1. Grasp recognition from raw EMG signal.

For the laboratory stage of the work, a standard PC running Windows is being used. A USB interface connects the PC with the ADCs and EMG electrodes.

Figure 1 shows the flow of data from raw signal through to the identification of a grasp. The information obtained from electrodes on the forearm undergoes filtering to isolate the usable spectrum of the EMG signal. The next phase is feature extraction, where the overall multichannel signal is described by a smaller set of data. This information is then used for either training or classification purposes. When a subject uses the electrode system for the first time they need to train the software to recognize their muscle movements. This is accomplished by getting them to repeatedly perform each of the six grasp types to be identified. The data obtained during these movements is saved for offline processing where it undergoes multiple feature extraction techniques. The pattern recognition phase uses the extracted features as the training set for either a neural network or as the basis for statistical identification.

It is accepted that not every user will get the best results from the same feature extraction and pattern recognition techniques. For use of the system as either a prosthetic controller or a bioelectric interface, the user needs to have complete confidence in the system. Therefore successful grasp classification rates of above 90% are desired after initial software training. When the user has had experience using the system they will also adapt with their muscle movements becoming more consistent thus leading to even higher recognition rates.

The algorithms used in the identification process also have to be fast. For real-time hand control a maximum of 200 milliseconds for classification is suitable. Too long a delay in enacting the required grasp will make the system impractical. There is a trade-off between processing time and classification success rate. A complicated algorithm might be very accurate but may take too long to be practical.

There is also the issue of muscle selection, for able-bodied users the same muscles can be used for all subjects but amputees will have varying degrees of muscle removal depending on the level of amputation. In some cases it will be necessary to choose different electrode locations which may not provide as much information as the typical site selection. These users will need to undergo more extensive training to reach suitably high levels of correct grasp classification.

3 Instrumentation

The first stage of the project was to get a signal from the forearm muscles. This analogue signal then needed to be sampled and made available to software on a standard desktop PC.

3.1 EMG Electrodes

Muscle contraction is created by twitching of muscle fibres, the level of contraction being determined by both the number of fibres activated and the rate at which they twitch. A single motor unit is a collection of a number of muscle fibres activated by a single neuron. The electrical potential of individual motor units can be measured with fine wire or needle electrodes to determine the level of activity present. While these electrodes are widely used in clinical applications they are unsuitable for the practical applications under consideration. The EMG signal as measured at the skin surface is the spatial and temporal sum of individual motor units within multiple muscles in the vicinity of the recording electrode. The signal is stochastic with a typical amplitude of 0-6mV. The usable frequency range is 0-500 Hz with most energy concentrated from 50-150 Hz [De Luca, 1997].

Ambient electrical noise is a serious problem as the human body is an excellent antenna and the amplitudes of this noise, particularly in the 50Hz range, are far greater than the EMG signal. Unfortunately this is exactly the area of the EMG spectrum where the most useful information is located. For our system we found the best results were obtained by using instrument amplifiers with a high CMRR (120dB) and feeding the inverted common-mode signal from each electrode pair back onto the arm (Figure 2). This very effectively cancels out all unwanted electrical signals, there has been no need to carry out any 50 Hz filtering after gathering the signal.

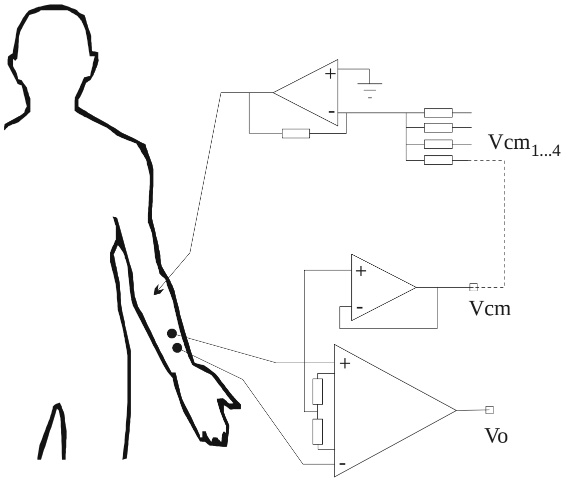

Figure 2. EMG instrumentation showing electrode pair and feedback of common-mode signal to arm

For the electrodes a system using disposable silver/silver chloride disc electrodes was initially used but this proved inadequate for several reasons. These needed to be applied in pairs at specific locations on the skin. Repeatedly locating electrodes at the correct spot is essential as even small differences in location can lead to large changes in the resulting signal. Positioning the disposable electrodes accurately proved a difficult task. An electrolytic gel needed to be used with the silver/silver chloride discs to establish electrical contact with the skin tissue. This led to the electrodes slipping on the now wet skin surface. This caused motion artefacts in the signal, these appeared as large voltage spikes whenever one of the disposable discs moved. The other major problem with this system was that amplification of the signal was performed some distance from the actual electrode surface. Because the EMG signal has such a low amplitude this meant that electrical noise induced in the connecting cabling could significantly degrade the signal.

Active Electrodes

To counter many of these problems an active electrode system was developed. To improve the signal-to-noise ratio it was desired to have amplification occurring as close as possible to the electrodes themselves. A fixed geometry of the electrode surfaces would assist in relocating the electrodes at the correct location. If the electrodes could be applied dry, without any conductive gel, this would aid in the application phase as well as reducing the likelihood of motion artefacts appearing in the signal.

Guidelines for electrode geometry were obtained from De Luca [1997] and resulted in the creation of the *active electrode*[1] shown in Figure 3. The electrode detection areas consist of two gold plated rectangular surfaces on the bottom of a small board containing the amplification circuitry. These each measure 10mm x 2mm and are spaced 12mm apart. These bars are placed on the skin surface parallel to the direction of the muscle fibres.

[1] De Luca defines an active electrode as an EMG sensor where the differential amplifier is located as close as possible to the detection surfaces.

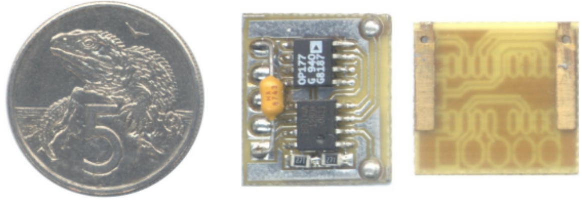

Figure 3. Active electrodes with NZ 5c coin for scale.

As illustrated in Figure 2 each surface is connected to an instrumentation amplifier and the output voltage (Vo) is sampled by the computer. The common mode voltage (Vcm) of all electrodes is fed into a summing amplifier and the resulting inverted signal is then fed back onto the arm. Usually a silver/silver chloride electrode is used as the connection for this. It is placed at a point on the skin with minimal underlying muscle, typically in the elbow region.

Muscles

Each electrode is placed above a specific muscle in the forearm. The system developed can handle up to eight electrodes simultaneously. Typically four electrodes are used, placed on extensor muscles of the upper forearm. Vuskovic *et al.*, [1995] use these as they are associated with the preshaping of the hand. Extensor Pollicis Longus and Extensor Pollicis Brevis are responsible for thumb movement. Extensor Communis Digitorum is related to index and middle finger motion while Extensor Carpi Ulnaris indicates little finger activity.

This selection is suitable for able-bodied subjects but amputees will not necessarily have all these muscles intact.

3.2 Computer Interface

The output from each active electrode is fed into a custom made A/D converter sampling at a rate of 2000 Hz. A USB connection is used to enable the hardware to be easily used with any modern desktop PC. Data is stored in a buffer after sampling, with the computer being able to retrieve information at any stage. This eliminates the need for a real-time operating system.

Software

Initially all data processing was done offline using MATLAB. EMG data was recorded straight to hard disk for later use. More recently all programming has switched to C++ in a Windows environment. With faster computer hardware it has been possible to display a plot of the incoming multichannel signals. This is a very useful aid when locating electrodes on the user’s arm as it is possible to see where the best signal is being obtained.

Once electrodes are properly positioned the display can be switched off in order to allow the computer to perform the task of identifying the grasp being enacted.

4 Grasp Recognition

For the control of a robot hand we aim to identify the basic grasp shape being made by the user. In order to grasp and manipulate an object the human hand will first form a basic shape suitable for gripping the required item. This phase is known as *preshaping*. Once the style of grip being enacted is known the robot hand is commanded to move the fingers to the correct orientation. Recognizing this initial shape is the first task, completing the grasp can then be accomplished using feedback sensors within the fingers [Vuskovic *et al.*, 1998].

4.1 Grasps

There are a number of basic grasp shapes that the human hand can form. There are many studies each with their own definitions of a basic set of grasps, an extensive list is available [MacKenzie and Iberall, 1994]. We have settled on those used by Vuskovic *et al.*, [1995]; large and small cylindrical, large and small spherical, pinch and key as illustrated in Figure 4.

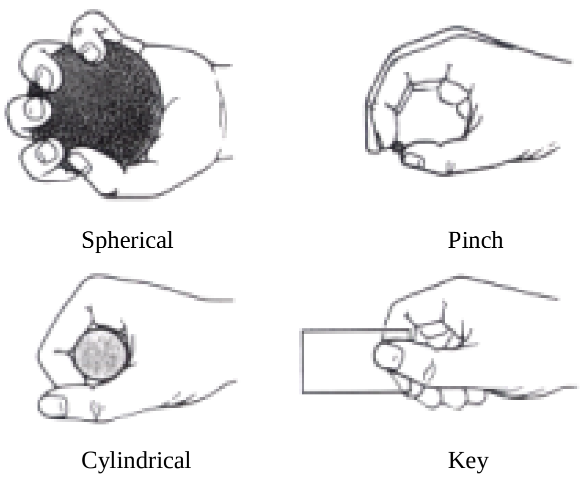

Figure 4. Basic grasp shapes

4.2 Feature Extraction

The quantity of data being gathered makes it cumbersome to work directly with the raw EMG signal at the pattern recognition phase. The strategy is to reduce this information down to a smaller set of identifying characteristics by means of various feature extraction algorithms. The information extracted is still enough to describe the signal, but with a smaller set of data.

Each channel of the raw EMG signal is a discrete time series $y(k)$. Many methods have been trialled to characterize this time series for later pattern recognition. Simple methods such as moving average filters and zero-crossing rate have been looked at but only provided low grasp recognition rates.

Frequency Domain

Looking at the signal in the frequency domain reveals useful information which can be used to identify the signal. The Short-Time Fourier Transform (STFT) breaks the incoming signal into small blocks and performs an FFT on each segment. This gives a measure of both time and frequency information, showing at which point in time the various frequencies are occurring. There is a trade-off between frequency and time resolution. To increase time resolution, smaller segments of data must be used which decreases the resolution of the resulting FFT. In using this technique for feature extraction, many different segment sizes and overlapping time windows were trialled. The resulting data set is still quite large but does give greater recognition rates than a filtered time series.

Parametric Modelling

The power spectrum of the EMG signal can be described as a pole-zero model. An autoregressive (AR), or *all-pole*, model was used to model the time series as:

$$y(k) = -\sum_{i=1}^{P} a_i y(k-i) + e(k)$$

Where a_i are the AR coefficients, P is the order of the model and $e(k)$ an error term. The incoming signal is divided into overlapping segments, as in the STFT, and the AR coefficients computed for each segment. Various window lengths and model orders have been tested. The best results are obtained from a model of order P = 20 with a window length of 256 samples.

Wavelet Decomposition

An interesting field of mathematics which has been applied to many different practical applications is the use of wavelets. These provide a method of extracting time-frequency information from a signal.

The Discrete Wavelet Tranform (DWT) is a fast, linear operation. It is similar to the FFT in that can be viewed as a rotation in function space that tranforms the time domain to a different domain. With the FFT the new domain has basis functions of sines and cosines while the DWT bases are more complicated and known as *wavelets*. There are many different families of wavelets and several of these were investigated.

Deconvolution

One method trialed involved an attempt to deconvolve the surface EMG signal to find the underlying train of pulses sent from the nervous system to the muscles. It was thought that this would provide an easily recognizable pattern for each grasp. While this worked well for a simulated signal its effectiveness reduced with the introduction of even a small amount of noise. When applied to real data it proved completely ineffective. It is an interesting approach but is unsuitable for surface electrodes.

4.3 Pattern Recognition

Once the incoming signals have been reduced in the feature extraction phase the next step is to identify this data based on pretrained information. The training phase involves applying EMG electrodes to a subject while getting them to repeatedly perform each of the six different grasp types. This data is all recorded, then the various feature extraction techniques are performed on it. The resulting information is to be used as the training set for either a neural network or a statistical model. This forms the basis for identifying grasps made by the same user.

There are several different options for pattern recognition. There are many kinds of neural network which are suitable for this application, and there are also statistical methods. Both these types of identification have been used with mixed success.

The statistical methods were based on those used by Elliott, [1998] and Vuscovic [1995]. These involve classifying an unknown vector as belonging to a cluster to which it is closest. The clusters are based on values obtained from the training data set. Deciding which cluster is 'closest' to the vector is made by selecting an appropriate norm. The Euclidean, Mahalanobis and Transformed Euclidean norms were tested in Elliott [1998], with the Mahalanobis distance providing the best results in that study. This method was used during this project. It has proved quite effective and has some advantages over the neural network apporach, mainly in speed of training.

For the neural network pattern recognition a two layer network with back propagation learning was used. During the training the convergence of the learning process took a substantial amount of time while offering results similar to those of the statistical clustering. Back propogation networks are unsuited for incremental learning, so once trained there is not much scope for changing the network.

5 Results and Future Work

The major testing at this stage has involved data gathered with the original EMG electrode system being processed offline. Successful recognition of grasp varies with the individual subject being tested, the feature extraction technique and parameters used during this phase, and the pattern recognition method and parameters.

Mean values of the success rates are around 75-80% depending on which features and extraction parameters are being used. So far there has been no one technique has performed consistently highly for all test subjects. Some techniques work well on certain subjects, but no better than average on others.

For this reason it has been decided not to rely solely on one algorithm for all users. During the training phase each user now records a substantial amount of data. The entire data set undergoes multiple feature extractions of different types. A subset of these results is used to train the pattern recognition stage, while the remaining data is used as a test of the recognition success. Based on the results of these tests the best performing feature extraction algorithm is selected and used for online testing with that user. Online testing is where the computer software identifies the grasp as the user is making it, rather than working with pre-recorded data. As the user becomes more familiar with the system they will also adapt their movement patterns. This should lead to a very reliable, easy to use system.

Acknowledgements

The authors would like to acknowledge the technical support of Mr Andy Cree, and Mr Rodney Elliot, scientific officers in the Mechanical Engineering Department of University of Canterbury, New Zealand.

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