# LOW-COST, REAL-TIME EMG SIGNAL PROCESSING FOR PROSTHESIS CONTROL USING DYNAMIC PATTERNS

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## ABSTRACT

In this paper an approach to control a 3 degrees of freedom (DOF) below-elbow prosthesis is presented. Myoelectric patterns generated by flexor and extensor muscles during the initial phase of muscle contraction are used. It has been shown by previous researchers that specific "dynamic" patterns exist during this period. The aim of this work was mainly to achieve high classification success rate with a minimum mathematical complexity in order to reach a low-cost upper-limb prosthesis design. A special purpose hardware based on an Intel 87C52 microcontroller has been developed. EMG signals are amplified by an instrumentation amplifier and band-pass filtered before being digitized by an A/D converter. A serial link to a PC allows (in an off-line mode) the setting of different parameters such as sampling rate and feature to be extracted. The mean absolute value (MAV) of the EMG computed over windows consisting of 5 samples was used as a feature. Only the first 160 ms of the EMG was used because during this period obtained patterns show good separability. A new motion was detected when the sum of MAVs from both channels exceeds a preset threshold value. 4 healthy subjects participated in these experiments, each of the 6 reference patterns being computed by averaging 50 measurements (in total 600 segments of the EMG signal lasting 160 ms each were used). With an Euclidean minimum distance classification scheme and short-time training, a 95.3% success rate for 3 DOF was obtained. The computations were all done in real time by the above described hardware.

## INTRODUCTION

The electromyogram (EMG) signal is a weighted superposition of many motor unit action potential trains (MUAPT) that are independently triggered. Proposed models for this signal suggest a nearly gaussian distribution with zero mean [1] and with a variance directly related to the contraction level [2]. This last property is used in many myoelectric control systems as the input parameter for motion identification. Newer research has shown that the myoelectric signal exhibits a deterministic structure during the initial phase of the muscle contraction [3]. Signal averaging is a powerful technique for separating random from deterministic components of signals which can be repeated several times [4].

In this work the properties of such patterns were first studied and then statistical pattern recognition methods were applied for classifying them in order to control a prosthetic arm with a low-cost hardware.

## METHODS

***Signal conditioning.*** The flexor and extensor muscles of the forearm are involved in all 6 basic below-elbow motions of the wrist (flexion, extension, pronation, supination) and of the hand (opening and closing). This pair of antagonist muscles are used in order to have a more natural relation between intended motions by the subject and actual EMG activity. Using two channels results in more information and therefore lower demand on classifier complexity.

EMG signals are amplified by two instrumentation amplifiers (AD524) with a CMRR of 120 db, passed through a 10 Hz second order butterworth HPF and a 300 Hz forth order LPF. These signals are then multiplexed and sampled by an 8 bit A/D converter (AD7569) with 1 KHZ sampling rate per channel. Digitized signals are send to an Intel 87C52 microcontroller running at 12 MHz. This particular microcontroller has been selected for its low power consumption (15 mA typical, and standby mode), small sensitivity to power supply voltage variations (20 % tolerance), internal RAM, EPROM, counter/ timers, full-duplex serial ports, 8-bit parallel ports and 8 bits integer multiplication/division in 4 s. The serial port could be used to send the EMG to a PC when the prosthesis is fitted, reducing electrode placement problems, troubleshooting, service and parameter initializing. These capabilities will be helpful for this application taking into account that the final aim is to integrate the hardware in the artificial arm in which a very small space is available.

***Classifier.*** Keeping in mind that the selected scheme for classification should be implementable by the available microcontroller, simple pattern recognition methods must be used for the real-time control. Statistical pattern recognition is used to classify measurement patterns between 6 classes of motions. Two kinds of measurement vectors are examined. The first type consisting of raw EMG samples of both channels received in the first 160 ms of the contractions (320-point vector). The second vector type is formed by computing 5 ms MAV from each channel acquired in the same 160 ms time, reducing the size of the vector to 1/5th of the raw vectors (64-point). Two general statistical pattern classifiers were applied to discriminate contraction patterns between 6 classes. The selection of these methods is based on the required computational complexity and capability of iterative calculations where the computations can be started just after receiving the first sample of a pattern. Especially, methods which require matrix operations are not used. The selected classifiers are:

*A. Minimum Distance Methods.*

Two definitions for distance are used. The **Absolute Distance (AD)** defined by:

$$d_A(M,Y) = \sum_{i=1}^{n} |m_i - y_i| \tag{1}$$

where $m_i$ and $y_i$ are the $i$th components of two n point vectors $\boldsymbol{M}$ and $\boldsymbol{Y}$ respectively.

and the **Euclidean Distance (ED)**:

$$d_E(M,Y) = \sqrt{\sum_{i=1}^{n} (m_i - y_i)^2} \tag{2}$$

*B. Matched Filter Classifiers.*

A simple matched filter is the inner-product (IP) or correlation classifier. The output $g_k(Y)$ of the kth filter is the inner product of the input pattern $Y$ with , $M_k$ the mean vector of the $k$th class:

$$g_k(Y) = |Mk|\ |Y| \cdot Cos(\angle Mk, Y) = M_k^T \bullet Y \tag{3}$$

where $Mk$ is the mean vector of the class $k$. The winner class is the one which produces the maximum filter output. If the covariance matrices of all classes are equal to a multiple of the identity matrix and all mean vector lengths are equal, this classifier is the optimum minimizing the probability of error [5]. A second matched filter which does not require equality of the mean vector lengths can be defined as:

$$g_k(Y) = 2 M_k^T \bullet Y - |M_k|^2 \tag{4}$$

It can be shown that this equation can be used for ED classification. Because of the better accuracy obtained when working with quantized values, equ. (4) will be used instead of equ. (2) for classification.

The reference vectors (mean vectors) of the 6 classes are computed by averaging 50 records of pattern vectors. For the IP method these vectors are also normalized to equal lengths.

***Protocols:*** 4 healthy male subjects with ages between 18-26 years old were selected for evaluating the performance of the classifiers. They were asked to do 50 similar contractions for each of the 6 below-elbow motions. These records were used as a training set for computing the reference vectors. They were then asked to do 300 more contractions (50 contractions for each class) in a random order dictated by a uniform random generator program. All 3 classification methods (AD, ED and IP) were applied to these patterns and the success rates for different cases evaluated. Less than 1 hour per subject is required for familiarization with the system and data acquisition.

## RESULTS

Fig. 1-a shows a 200 ms segment of the EMG from the forearm flexor muscles during the initiation of contraction for hand closing. To detect any deterministic component in this phase of contraction an ensemble average of 20 similar records is shown in Fig. 1-b. The contraction was maintained at the same level by trying to do the actions in the same way. The random part of the signal is averaged out in this way and the deterministic structure appears clearly after 50 sweeps (Fig.1-c). More examinations of other wrist and hand actions showed that each contraction type has a different pattern.

The alignment of records for averaging is based on the level of myoelectric activity. Before starting a contraction the muscles are relaxed and the EMG amplitude is near zero. At the time of starting contraction this activity increases. This property is used for aligning several patterns before averaging. The MAV is computed continually with a short window of 5 ms. This length is selected experimentally, smaller values resulting in the risk of triggering with an unwanted EMG spike, while greater values lead to more alignment error. A contraction is detected when a pre-specified threshold is exceeded. This window width results in about 5 ms uncertainty in detecting the start of the patterns, leading to a smoothening of fast varying components hence weakening of higher frequencies.

***Effect of vector type:*** Fig. 2 compares the average success rates when raw EMG vectors and MAV vectors are used for subjects HD and RD. Although MAV patterns seem to have lower information than raw EMG patterns, they are more successful. This is patly due to the more sensitivity of the EMG vectors to alignment. This could also be an indication that actual dynamic patterns have a lower spectra than other random components of the EMG so that the low-pass filtering effect created by MAV computations has enhanced the signal to noise ratio. Thus the MAV patterns will be used in all subsequent experiments.

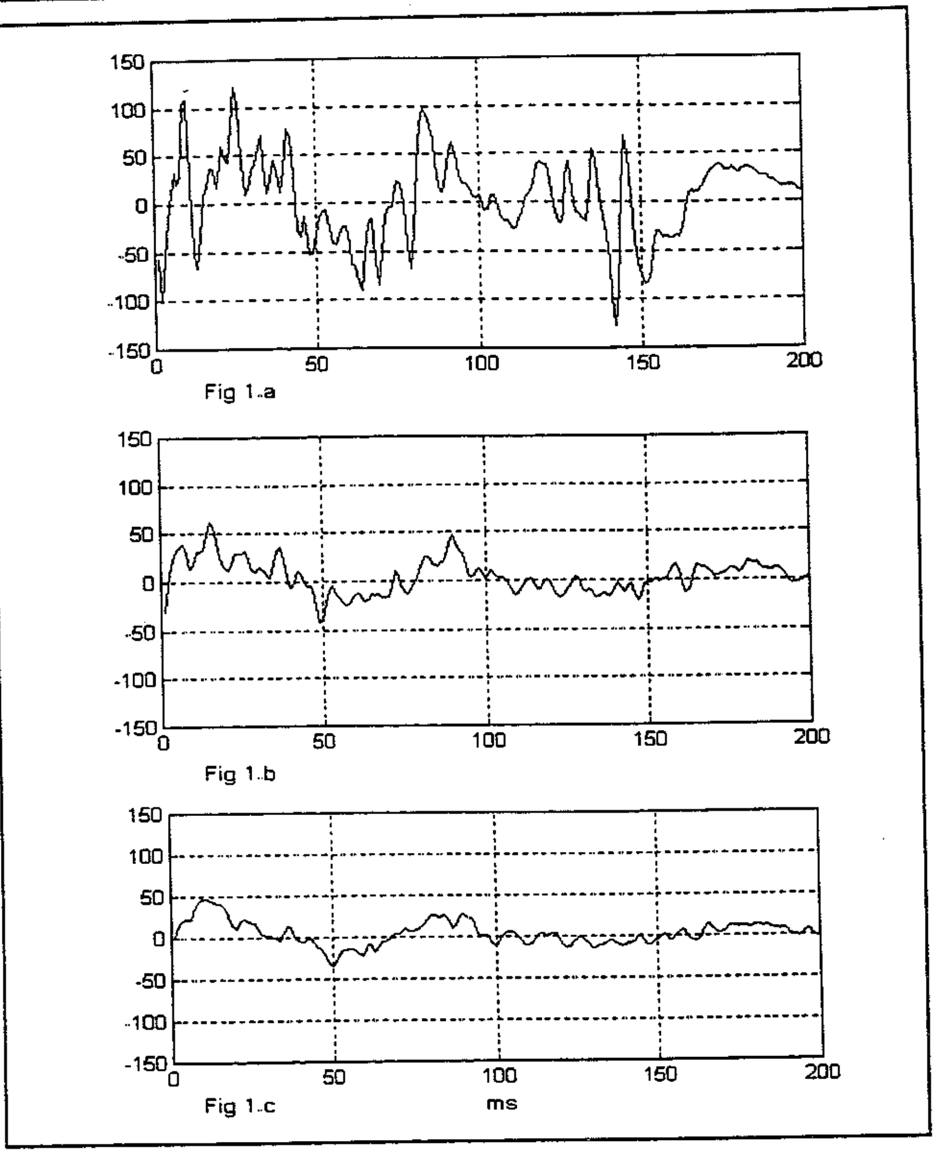


*Fig. 1. EMG signal from forearm flexors during initiation of hand-closing. a- single sweep, b- average of 20 sweeps, c- average of 50 sweeps*

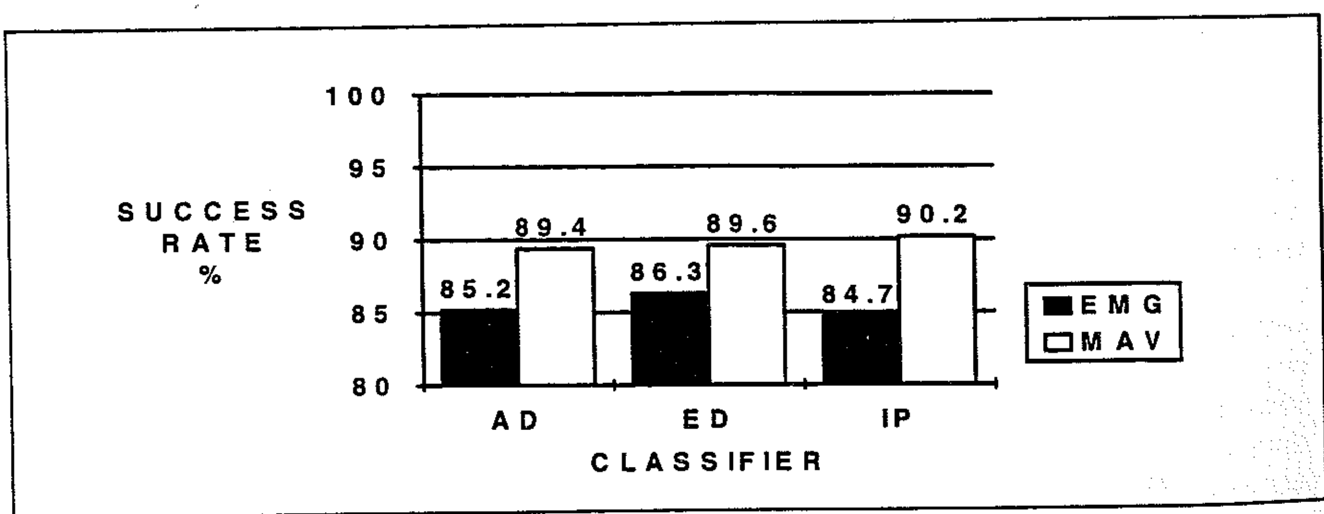


*Fig. 2. Average success rates for two subjects (HD and RD) for raw EMG and MAV.*

***Success rates for different classes:*** Table1 shows success rate averages for 6 types of contraction for all subjects and by classification method.

| CLASSIFIER | FLEX | EXT | PRON | SUP | OPEN | CLOSE | AVERAGE |
|---|---|---|---|---|---|---|---|
| AD | 96.5 | 81.5 | 79.0 | 85.0 | 89.5 | 97.5 | 88.2 |
| ED | 94.5 | 80.5 | 84.5 | 87.0 | 87.0 | 99.0 | 88.8 |
| IP | 96.0 | 88.5 | 87.5 | 87.0 | 82.0 | 93.5 | 89.1 |

*Table 1. Success rates for different classes (three different classifiers).*

***Success rates for different subjects:*** Fig. 3 shows the success rates for each of the 4 subjects. Personal skills of the subjects affect this results.

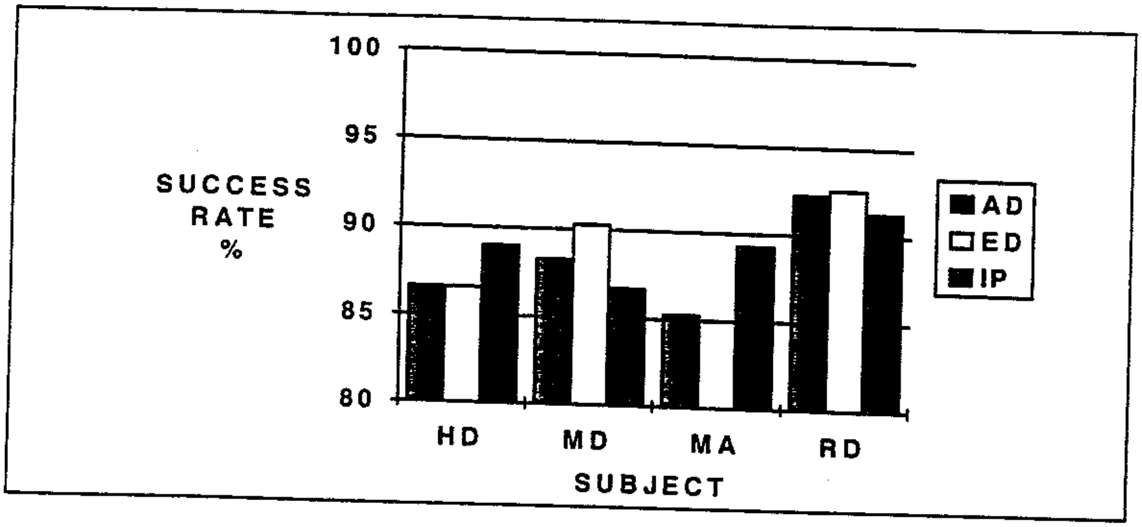


*Fig. 3. Average success rates for different subjects for three different classifiers.*

***Effect of training:*** One subject (HD) was asked to repeat the tests for 3 successive days for about 1 hour per day, in order to contract the involved muscles in the same manner. After these 3 days the new reference vectors replaced old ones. Then new tests were done as before. Fig. 4 compares success rates obtained by this subject before and after training.

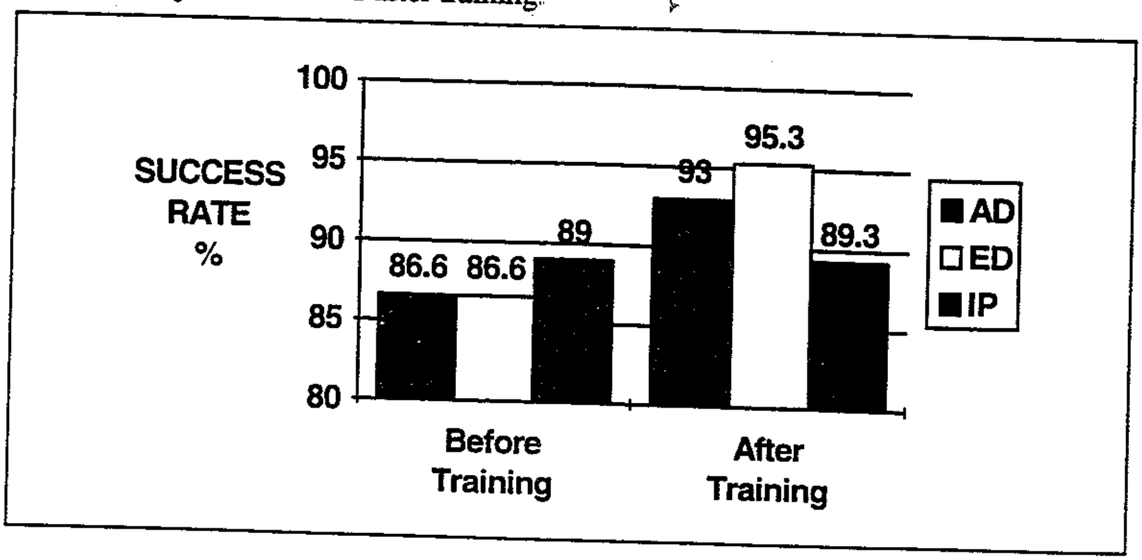


*Fig. 4. Success rates for subject HD.*

For each of the classification methods only less than 5 percent of the CPU time is needed for all data acquisition, classification and determination of the intended motion.

## CONCLUSION

The MAV has been successfully applied to EMG pattern classification for prosthetic control. The main advantage of such a feature is the success rate (95.3) obtained by classical pattern recognition methods implemented in real-time by an off-the shelf microcontroller. The Euclidean distance classifier showed best results after training. This approach is thought to be a significant step toward smart artificial arms, in which minimum mental effort and training is needed to fit the prosthesis.

Future research will focus on the application of this method to amputees and the experimental determination of procedures needed to select the optimum MAV window length. Some minor modifications (such as the use of a battery back-up RAM) in the hardware can assure the independence of such a system even from a PC.

## REFERENCES

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