NEUROFUZZY LOGIC AS A CONTROL ALGORITHM FOR AN EXTERNALLY POWERED MULTIFUNCTIONAL HAND PROSTHESIS

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INTRODUCTION

We are developing a controller for a multifunctional hand prosthesis based upon multiple surface electromyograms (sEMG) using neurofuzzy logic technology. The sEMG signal is successfully used as a means of control in current commercially available myoelectric prostheses. However, these are either single degree-of-freedom (DOF) devices or sequential controlled devices with locking mechanisms to switch between DOFs. There have been several proposed algorithms of control extended to multiple DOF prostheses. Early myoelectric prostheses, such as the Sven Hand [1] and the Philadelphia Arm [2], involved the use of electrode arrays and used adaptive weighted filters to process the signals. More recently, Hudgins et. al [3] proposed extracting several parameters out of the first 200 ms of EMG activity in an effort to obtain a higher ratio of controllable functions to inputs. Other algorithms have also proposed control based upon pattern classification / feature extraction [4, 5] with the use of neural networks for system training [6], while others, specifically for hand control, have been based upon spectral analysis of the EMG signal [7]. These have met with varying degrees of success, but have for the most part been limited to laboratory success, and to our knowledge, have not been demonstrated as clinically practical solutions to the multifunctional control problem.

We propose an algorithm based upon neurofuzzy technology. We believe that because of the inherent “fuzziness” of human activity, a control algorithm based on fuzzy logic may have advantages for multifunctional prosthesis control. We seek an acceptable compromise between the number of electrode sites used and processing complexity, and thereby desire not more than three to four control sites to control three to four DOF. This approach delivers more information to the system and, by using fuzzy logic, reduces the complexity of the processing.

BACKGROUND

Fuzzy set theory maintains that all elements have a degree of membership (DOM) in all sets ranging from 0 to 1 inclusively. Figure 1 shows the difference in approach between fuzzy and classical set theories applied to the seasons of the year. A fuzzy logic system is composed of membership functions (MF) that fuzzify inputs, a rule set that governs how the system operates (see Table 1 for an example), and an output membership function that defuzzifies the system output. The advantage of such a system is that it is robust enough to handle small inaccuracies in data without significantly affecting the output. The system is clearly defined and modifiable, but not trainable.

Artificial neural networks (ANN) allow for system training based upon sample input data. As sample data is fed into the system, outputs are calculated by associating a degree-of-strength (DOS) to each input. The error difference between the desired and actual output is then back propagated through the system, and the DOS are adjusted accordingly. This learning process is characterized by the choice of learning method and the number of winner neurons, where the

![Figure 1: Seasons of the year according to classical set theory (top) and fuzzy set theory (bottom) [8].](image-url)
number of winner neurons is the number of DOS altered during one iteration. Such a system is advantageous because of this ability to be trained on sample data. However, this system is essentially a black box because it is not modifiable, nor are the parameters of the system intuitive.

Neurofuzzy logic attempts to combine the advantages of a fuzzy and a neural net system to present a system with clearly defined variables and parameters but with the ability to be trained. The fuzzy inputs are mapped to ANN input nodes, the fuzzy outputs to ANN output nodes, and the fuzzy inference system to hidden nodes, with connecting lines serving as degrees-of-strength (DOS) for the rule sets. As the ANN is trained, the DOS of the fuzzy system are altered, along with the parameters of membership functions, using the standard back propagation algorithm. For more information about fuzzy logic, ANN, and neurofuzzy technology, see [9, 10].

**EXPERIMENTAL PROTOCOL**

Muscles controlling wrist extension, wrist flexion, ulnar deviation, and finger flexion are located using standard clinical myotesting techniques. In ideal cases, we search for the extensor digitorum, extensor carpi muscle group, flexor digitorum superficialis, and flexor carpi muscle group. The main focus was to find three to four independent control sites. Other motions of interest were pronation, supination, and radial deviation. Upon location, a standard sEMG Ag/AgCl differential electrode is placed over each muscle in question.

All EMG data is collected using Noraxon’s telemeter Telemyo 8 System. The system records data at a rate of 1400 Hz, and applies a band pass filter (16 Hz low cutoff, 500 Hz high cutoff, gain of 2000) to the analog signals. For our purposes, individual gains are adjusted to obtain greater isolation of individual sites. The raw EMG signal, along with the associated signal RMS value (64 length sample collected at 1400 Hz), are collected, viewed, and saved in real-time on a PC computer running Labview 5.1.1. Ten seconds of quiescent data is simultaneously collected from all channels for reference. The subject is then asked to perform eight trials of each motion associated with each detected control site. Data is collected from the time prior to motion initiation until several seconds of steady state data are taken. Each file containing RMS values of the collected EMG signals is analyzed to determine the time instant of motion initiation by determining the first point in a series of five consecutive RMS points that are at least three times the quiescent RMS standard deviations (σ₀) above the quiescent RMS mean (µ₀). The initiation instants are verified through offline visual inspection and minor adjustments are made as needed. The data used to check the final fuzzy system is composed of all trials of all motions. The data used to train the initial fuzzy system is composed of the odd numbered trials of all motions. This procedure is followed to capture the effects of time and possible fatigue during the duration of the protocol. The results presented are for one subject without limb loss and one with a short trans-radial limb loss from birth.

**FUZZY SYSTEM DESIGN**

The fuzzy logic system is designed using Inform Technologies’ fuzzyTECH ver 5.52 MCU-320 edition development environment. This environment was chosen due to its ability to automatically convert designed systems into MATLAB, C, and assembly code for easy future implementation into a microcontroller of choice. Each input to the system consists of three membership functions (“low”, “medium”, “high”), where the points of intersection are determined by visual inspection of the “checking” data. The typical operating point of the corresponding input when its associated muscle function is isolated is chosen to be the value corresponding to unity membership in the “medium” membership. Following conventional fuzzy membership design, the “low” and “high” membership functions are then constructed such that there is fifty percent overlap between adjacent membership functions.

The fuzzy rules implemented are designed to cover all scenarios of EMG amplitude from inputs demonstrated by the “checking” data set. Thus, rules are first added for the case of complete input isolation (one and only one input is active). The next set of rules is added to cover cases of incomplete input isolation (more than one input is active). Because of the stochastic nature of the EMG signal, there exist cases where, upon initial observation, the same
set of linguistic inputs can produce different outputs. Thus, conflicting rules were also added into the initial fuzzy classification system, leaving resolution of these conflicts to the training process. The DOS of all rules are set to zero initially, effectively producing an unintelligent system. Using the back error propagation technique for system training, we looked at inclusion vs. exclusion of automatic membership function learning in the training process, and the effect of altering the number of winner neurons. The system with the minimum average error for each set of training parameters was saved. The same parameters that produce the highest accuracy for the normal subject data are then used to train data for the subject with limb loss.

RESULTS

Figure 2a shows the percent accuracy for all training parameter sets for data of the subject without limb loss. The system that produced the most accurate classification was the one that was allowed to modify the membership functions and the number of winner neurons was limited to one, resulting in a 99.15% classification rate. Figure 2b shows this system to be optimized after 85 iterations. Using the same parameters to train the system designed for data of the subject with limb loss, we achieved an accuracy rate of 96.57%.

![Image](image_url)

**Figure 2a:** Accuracy for each set of training parameters (MF = membership function).

**Figure 2b:** Error during training for the most accurate system. The system converges to the minimum error after 85 iterations. The results of over training can be seen after 160 iterations of training

Table 1: Final rule set and associated DOS for limb deficient subject data. The DOS determine the relative contribution of each rule to the system response.

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DISCUSSION

The high accuracy of classification for the subject without limb loss is encouraging in terms of possibly using this algorithm in a clinical prosthesis. There were several trials of motions
where the neurofuzzy system achieved excellent classification for the entire duration of the motion. This implies that it is possible for the classifier to be effectively trained and thus extremely accurate – the only requirement would be that the user would need to learn to repeatedly perform the desired motion in the same manner.

The classifiers presented here are limited in that they only allow for one DOF to be active at a time. However the concepts demonstrated can be extended into simultaneous classification (recognizing combinations of motions). This should be readily achieved through the addition of membership functions to the output and the implementation of another rule set that would cover the scenarios of simultaneous activity of multiple DOFs. The system would then again need to be trained with sample input scenarios.

Since the proposed classifier system makes a decision at time $t$ based solely upon RMS EMG information at time $t$, the conversion to a real-time system is straightforward. In addition, the short computation time required to process a fuzzy inference system is an advantage of such systems. This advantage is magnified by the fact that there now exists hardware dedicated to processing of fuzzy inference systems, such as the Motorola 68HC12 microcontroller family [11]. With further research, it is felt that the implementation of neurofuzzy technology as presented here may be applicable to practical clinical devices.

ACKNOWLEDGEMENTS
This work was supported by the Department of Veterans Affairs, Rehabilitation Research and Development Service and is administered through the VA Chicago Health Care System, Lakeside Division, Chicago, Illinois.

The first author was funded by the National Institute on Disability and Rehabilitation Research (NIDDR) of the Department of Education under grant number H133E980023. The opinions contained in this publication are those of the grantee and do not necessarily reflect those of the Department of Education.

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