

The Use of Fuzzy Logic In the Processing Of Myoelectric Signals

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1.1 ABSTRACT

This paper describes the use of Fuzzy logic for the processing of EMG signals. This can increase the recognition rate and significantly reduce the number of computations required to generate an output. The initial placement of the Fuzzy sets was accomplished with the use of neural network techniques, these are not required for in the final system, only for setting up. The effectiveness of the features extracted from the EMG signals has been assessed using Principal Component Analysis (PCA). The developed system exhibits good generalisability but performs better when tuned to the intended user.

1.2 THE PRINCIPALS OF FUZZY LOGIC

Fuzzy logic is the a relatively new technique for computing using vague linguistic concepts. It was developed in 1960 by Lofty Zadeh [4]. It is now becoming accepted as a method for solving difficult engineering problems. Fuzzy systems excel in complex well defined problems, for instance the problem of target tracking. An implementation of this is designed with a Kalman filter and has a very rough transfer plane where as one that is implemented in Fuzzy Logic has a much smoother transfer plane and also uses much less computational power.

Conventionally most computing is performed on real, precise concepts. A computer has no concept of "tall" or "short", this is a human construct. In spite of the fact that they are inherently vague we still manage to communicate significant amounts of information using these terms. Fuzzy logic encodes this vagueness. It allows a value to be a "member" of a group. The "membership" of the group is defined as how much the value belongs. It is usually in the range 0 to 1. So using the example of membership functions in Figure 1.1a a value of 20 would be a member of Zero 0.5 and Low 0.5. The value is therefore a member of two groups, this fact is retained until the final defuzzification. While the inputs are "Fuzzified" they are operated on by a set of rules. The rules define the behavior of the system they map the input sets to the output sets. At this stage there maybe multiple active output sets it is not until the outputs are defuzzified that the output becomes real valued. This is a simple overview of a fuzzy system for a more detailed approach see [2]

1.3 THE EXPERIMENTS

Data was initially collected from normal healthy volunteers, usually from the forearm around the region of the Flexor carpi radialis, Palmaris longus and the Flexor carpi ulnaris. Later, users of upper limb prosthesis were also recruited. The volunteers were required to produce

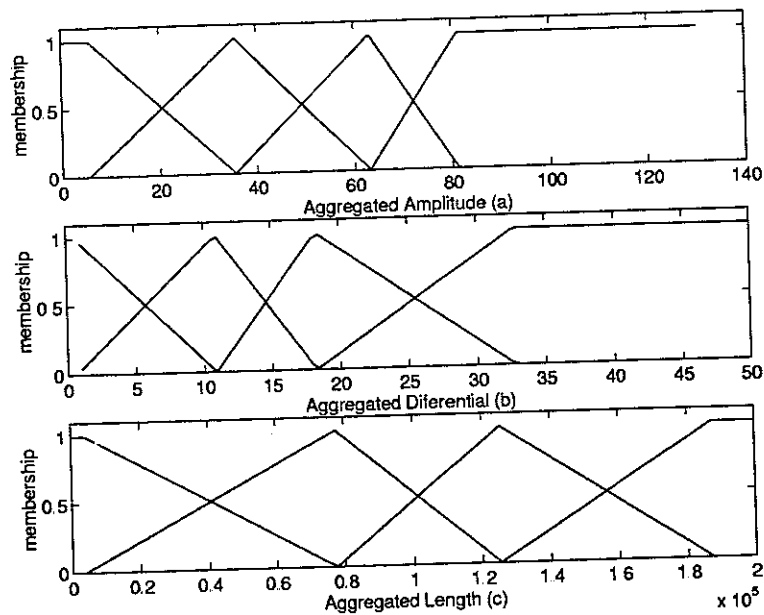


Figure 1.1: The Fuzzy Membership Functions (a) Average amplitude, (b) Averaged Differential, (c) Waveform Length

three distinct contraction levels and a zero. All subjects managed this with little or no training. For the able bodied volunteers the force level was also recorded using a simple force bridge. This enabled a verification of the force level in the early stages of development. Twenty contractions of two seconds duration were recorded from each subject for each level. For the processing of the data the start of contraction was ignored. This avoids the problems associated with determining and detecting the start of contraction. As the target system is contraction level driven this is unlikely to present a significant problem in a real time system.

1.4 SIGNAL PROCESSING

The system decoded four levels, of EMG activity (including rest). These levels corresponded to distinct, increasing force levels in the able bodied users. In order to process the data, the amount of information in the signal has to be reduced. This was achieved through feature extraction. Similar features to those used by Hudgins [1] were extracted from the signal. The amount of information contained in these features was verified using Principal Component Analysis (PCA). This allows the amount of information contained in the data to be visualised easily, therefore making the assessment of the features' information content simple.

1.4.1 Placement Of The Sets

The optimal placement of the Fuzzy sets was achieved with Kohonen Clustering. This is a learning algorithm that moves the "center node" to the centre of a cluster. This is a standard

neural network technique which produces optimal clusters in N dimensional spaces [3]. The cluster centres were then used as the focus points for the fuzzy membership functions.

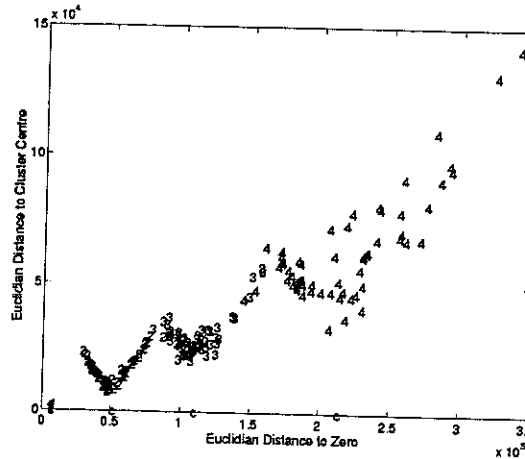


Figure 1.2: Kohonen centres with 4 nodes and the classifications of the Training data set

1.4.2 Fuzzy Analysis

The Fuzzy system aggregates the results from the fuzzification of the different features, but still retaining essential information. In comparison a Kohonen Network or Radial Basis Function Neural (RBFN) network would have to process one long vector. This would be composed of the individual feature vectors, resulting in long processing delays. Fuzzy logic provides a shorter route from the combination of the information extracted from the signal to an output. The production of a real valued output or defuzification is relatively simple as the output is discrete steps. The simplest form of defuzification was used, the maximum value from the Fuzzy processing was taken as the output.

1.4.3 The Features

The features extracted from the signal are as follows: Average Amplitude, Average Differential and Waveform Length. These are computed over a 200ms window of EMG data. ([1]).

1. *Mean Absolute Value.* This gives an indication of the amplitude of the signal.

$$\bar{X}_i = \frac{1}{N} \sum_{n=1}^N abs(x_n) \quad \text{for } i = 1, \dots, I \quad (1.1)$$

where x_n is the n^{th} segment and I the total number of segments in the entire sampled signal.

2. *Waveform Length*. This is an indication of the activity of the signal, it is the sum of the absolute values of the signal over the window length.

$$L_i = \sum_{n=1}^N (abs(x_n - x_{n-1})) \quad \text{for } i = 1, \dots, I \quad (1.2)$$

3. *Zero Crossings* The number of times the signal crosses the zero axis within each window.

$$Zc_i = \sum_{n=1}^N \text{sgn}(-x_i * x_{i+1}) \quad \text{for } i = 1, \dots, I \quad (1.3)$$

$$\text{sgn}(x) = \begin{cases} 1 & \text{if } x > 1 \\ 0 & \text{otherwise} \end{cases}$$

4. *Differential*. This is the average differential within the window. Hudgins uses the difference between successive windows (equation 1.4) but as the signals that the system were trained on were constant, the average differential within the window was used (equation 1.5). The difference between successive windows was minimal when using Equation 1.4.

$$\Delta \bar{X}_i = \bar{X}_{i+1} - \bar{X}_i \quad \text{for } i = 1, \dots, I - 1 \quad (1.4)$$

$$D_i = \frac{\sum_{n=1}^N (x_n - x_{(n-1)})}{N} \quad \text{for } i = 1, \dots, I \quad (1.5)$$

Equation 1.5 gave a better indication of the activity of the signal.

1.5 RESULTS

The results are displayed in table 1.5. When trained on three subjects the system performed well, yielding a 84% classification rate including the test signals. The test signals were not used in the training of the system. The system was optimized for one subject, (yielding a 100% classification rate) the total classification for the test data set was 95%.

Method	Classification Rate			Overall
	Training Data individual	all	Test Data all	
Kohonen Network	84%	97.1%	93.3%	95.2%
RBFN	94%	Na	79%	86%
Fuzzy Nwk	Na	92%	76.7%	84.4%
Opt Fzy Nwk	100%	Na	93.3%	96.7%

Na = Not applicable

Table 1.1: Classification Performance

1.5.1 Feature Analysis

The extracted features were analysed with PCA, figure 1.3 is a plot of the first Principal component vs. the second PC. The figure demonstrates that the features are separable in the higher order PC therefore they are useful for separation of different force levels. As it is not possible to completely separate the features other features have to be used to add information. All the features were assessed in this way. However, Zero crossings when analysed this way, does not contain any useful information.

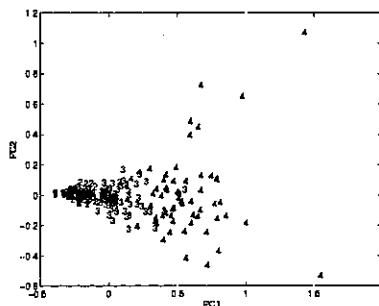


Figure 1.3: PC1 vs PC 2 for Average Differential

1.5.2 Computation Time

To evaluate the increase in computation efficiency the number of Floating Point Operations (FLOPs) required to produce a result was recorded for the different algorithms. This gives a relative measure of the native performances of the algorithms. The number of FLOPs is detailed in Table 1.2. The Fuzzy system performs nearly ten times faster than the Kohonen Network. The RBFN though having a higher classification rate requires many more FLOPs to achieve the same result.

	One Feature	Three Features
Kohonen Nwk.	480	1440
RBFN	34200	88000
Fuzzy Nwk.	Na	366

Table 1.2: Number of Floating Point Operations to produce an output

Bibliography

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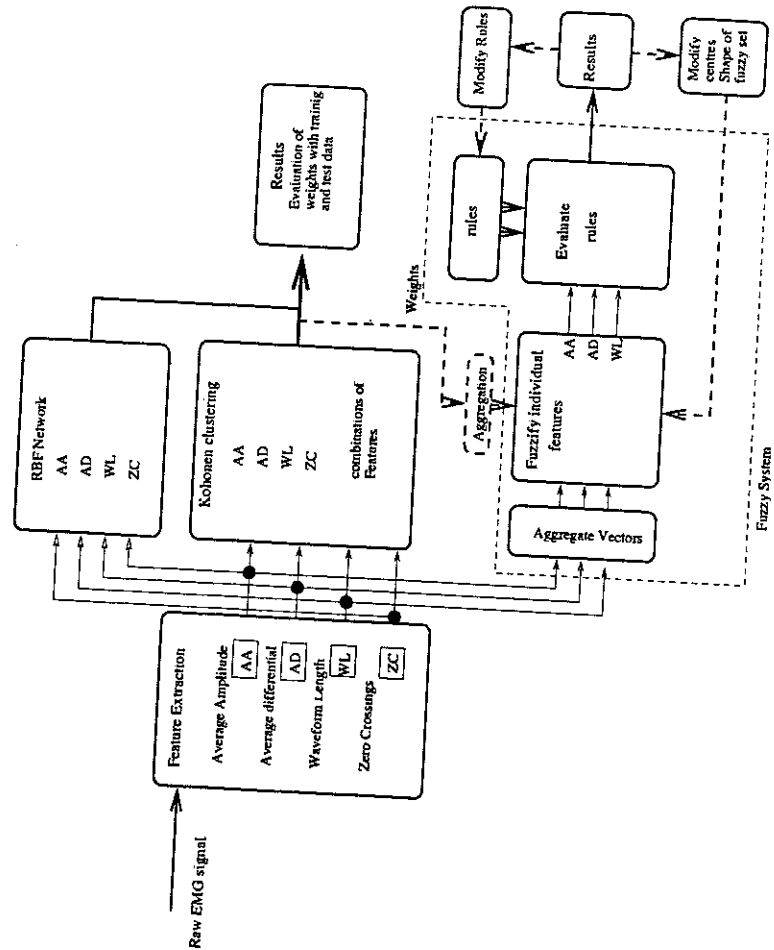


Figure 1.4: The Flow Diagram of the Fuzzy System and Neural Network Based Components

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