Application of Neuro-Fuzzy Systems to Behavioral Representation in Computer Generated Forces

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Key Words:
Neuro-fuzzy systems, soft computing, fuzzy sets, neural nets, computer generated forces, human modeling, manual tracking

Abstract

A new mathematical modeling technique known as soft computing is showing promise in modeling complex human behaviors. This paper will discuss the theoretical concepts of a soft computing technique, neuro-fuzzy systems. This technique has direct application to behavioral modeling of synthetic forces. Furthermore, the paper will present a specific experiment and modeling of the human operator's behavior. In the compensatory task the human has the error displayed and he attempts to null it to zero in the presence of random disturbances in the control process. Results will be presented demonstrating the validity of the hybrid modeling approach. This type of human behavior requires the modeling of perceptual, cognitive and motor processing.

1.0 Introduction

Behavioral representation in synthetic forces is the modeling of human behavior as it relates to military roles and missions. These models should incorporate the spectrum of human biomechanical, physical, psychophysical and psychological parameters, responses and interactions. Synthetic battlespaces are comprised of physical (aircraft, sensors etc.), environment (weather, dynamic terrain etc.) and these human models. Currently the human models are not as sophisticated as the physics based physical and environmental models. This is in part due to the fact that human behavior represents highly complex nonlinear and adaptable systems. Conventional approaches of state machines and expert systems have been applied to computer generated forces (CGF). The result in some cases has been synthetic force portrayals that are not totally autonomous, are unrealistic and do not support the full DoD requirements for analysis and training.

A new mathematical approach known as soft computing (SC) is emerging that shows promise in dealing with the inherent complexity of modeling human behavior. SC is a discipline situated at the combination of several relatively new and distinct mathematical techniques: fuzzy logic (FL), neural networks (NN) and probabilistic reasoning (PR) which include genetic algorithms, chaos theory, belief nets and learning theory. Soft computing differs from conventional computing in that, unlike hard computing, it is tolerant of imprecision, uncertainty and partial truth. In effect, the role model for soft computing is the human mind. The guiding principle of soft computing is: the tolerance for imprecision, uncertainty and partial truth to achieve tractability, robustness and low solution cost. What is important to consider is that SC is not an uncoordinated combination of

FL, NN and PR. Rather, it is a partnership in which each contributes usually at different organizational levels providing a hybrid system. In this perspective, the principal contributions of FL, NN and PR are complementary rather than competitive.

One hybrid system that is the most visible today is neuro-fuzzy systems which applies a combination of artificial neural networks (ANN) and fuzzy systems. ANN's have been employed in several applications ranging from target recognition to financial forecasting. Their most prominent feature is to learn from examples, then adapt themselves based on actual solution space training data sets. They are particularly powerful in clustering the solution space identifying important features. Fuzzy logic was founded by Lofti A. Zadeh in 1965 [1]. It is based on the idea that sets are not crisp but some are fuzzy, and these can be modeled in linguistic human terms such as large, small and medium. In fuzzy systems, rules can be formulated that use these linguistic expressions and apply them to the human behavioral problem. The combination of ANN and fuzzy sets offers a powerful method to model human behavior. The ANN is used to define the clustering in the solution space which result in creation of the fuzzy sets. The ANN learns these clusters based on actual human behavior test data. A further advantage is that the solution space rather than being represented point by point as some expert systems "clumps' the space as described by Kosko [2,3]. This results in fewer rules and lower computer resources.

The experiment to build and validate the model includes a compensatory task performed by several human subjects to develop a training and test set of data in this human behavior. In the compensatory tracking task the subject attempts to minimize a random error at a computer screen using a joy-stick. The compensatory tracking task is well suited as a model of everyday tasks such as vehicular control and the control of movements. For example when you drive a car along a road, avoiding the curb and remaining in the lane is performing a typical tracking task. From a military point of view target intercepts, glide slope following and laser designation are examples of compensatory tracking behavior. ANN's are used to find clusters in the training data that can define fuzzy rule sets for the modeling of the compensatory tracking behavior. The test set data was then used as input to the model to generate model output and then compared against the actual human output.

2.0 Soft Computing

The realization that modeling of highly complex systems, that require intelligent systems, must combine knowledge, mathematical techniques and methodologies from several sources. Intelligent systems such as CGF must possess humanlike expertise in the military domain. Like a human or a group of humans in a military organization they must be able to adapt and learn in a highly dynamic synthetic environment. This must be done within the constraints of doctrine, tactics, experience and performance of military systems. It seems reasonable that it would be advantageous to use several mathematical techniques together to form a hybrid system that leverages off the advantages of various modeling techniques. SC is the development of these hybrid systems that are also known as neuro-fuzzy computing [4,5,6]. This technique uses the power of artificial neural networks that classify patterns in data and adapt that classification with highly dynamic environments. Fuzzy inference systems are an extension of classical AI techniques that incorporate human knowledge and perform uncertain reasoning. In some cases genetic or evolutionary algorithms which are derivative-free optimization techniques may be applied to further complement the hybrid system especially in the NN arena.

In the toolkit for behavioral modeling of CGF there are the soft computing techniques as well as the classical AI methods. Each has specific technique has its strong constituents:

- Neural networks- Learning and adaptation of patterns in large amounts of data.
- Fuzzy set theory- Imprecise reasoning using fuzzy IF-THEN-ELSE rules.
- Genetic or evolutionary algorithms and simulated annealing- Systematic search using non-derivative methods.
- Conventional AI- Ability to do symbolic manipulation.

The key to SC is the ability to deal with uncertainty and learn to adapt to unknown and highly dynamic environments to improve performance. Furthermore, two of these techniques (neural nets and genetic algorithms) a are biologically inspired techniques. The National Research Council [7]

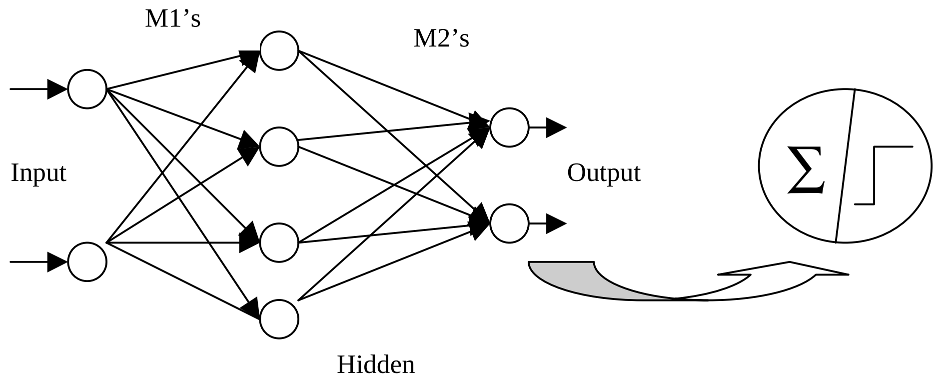


Figure 1 Neural Network Structure

study in 1998 concluded that biologically oriented modeling is an important direction for new behavioral modeling techniques for CGF. Lofti Zadeh, a leader in the SC field, [8] states it in this manner:

"*Soft computing is an emerging approach to computing which parallels the remarkable ability of the human mind to reason and learn in an environment of uncertainty and imprecision*"

George and Cardullo [9] applied SC to the human sensory integration modeling concept but to date little of SC [10] has been applied specifically to CGF behavior representation.

2.1 Neural Nets

The human mind is an amazing parallel processor. The brain processes incomplete and imprecise sensory information very effectively. NN mimic at a simple level the manner in which the brain processes information. These models are also known as connectionist models that attempt to use the organizing principles of the human brain. The NN consists of a number of independent processors (neurons) that communicate with each other. The neurons communicate with each other via weighted connections. Current research has been in the development of architectures of the NN, learning algorithms and application of these models to information processing tasks.

Figure 1 illustrates a simple feed-forward neural network showing the input, hidden and output layers. The lines between each neuron has an associated weight (M1's, M2's) that the output from the previous layer is multiplied by. In each neuron these incoming results from each input are summed and if the value is high enough the neuron "fires" and sends on the result to the next layer. Design considerations include architecture (number of neurons and hidden layers) and the type of activation functions.

NN's are trained by subjecting the network to input data from a process that classification or modeling is desired. There are two specific types of networks in this regard: unsupervised and supervised. In the supervised learning process input-output pairs of a process are used for training. The weights of the connections are adjusted such that the error of the NN output and the training set output is minimized. This creates a NN that now should approximate the real process with sufficient training and experimentation. In our application the use of unsupervised learning to partition the solution state space is necessary. In this case the NN is subjected to many input data sets and the connections adjusted based on the output neuron that has the highest activation output. The resulting weights after significant training then represent the centroids of clusters of data that can be used to define a fuzzy system representation of a system.

Consider Figure 2 for a simple example to illustrate clustering of state space data. This case has three inputs, a bias input for stability and 125 outputs. The network will be trained using the simplified Kohonen learning rules. The jth output neuron with the highest activation signal is the "winner" and corresponds to class Tj. The jth column of the weight matrix is then rewarded with this learning rule

$$M_j(k+1) = M_j(k) + c_k(X_K - M_j(k))$$
$$c_k = learningrate$$
$$X_K = input$$
$$M_j = jthcolumnM$$

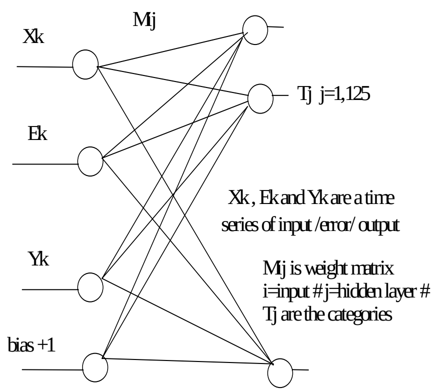


Figure 2 Unsupervised learning-clustering

and all other weights remain the same. The jth column is also known as the synaptic vector. The resulting weight matrix will contain the coordinates of the clusters in the problem space as represented by the 125 synaptic vectors. The counts of the winning neurons will be kept to examine the frequency of wins for each cluster. For clusters with a low number of wins they can be discarded and those fuzzy sets associated with that space not used in the model.

Consider a test case to illustrate the clustering. Consider a two input x-y input. the x and y are focused into two clusters that are normally distributed about two points in the x-y space (x1=10, y1=2 and x2=20,y2=5 with a normal distribution about these points). Using a two neuron input and six output units we can train the network and expect two of the six categories to approximate the two cluster centroids. For a run of 10000 (where x is uniformly distributed between 10 and 11, uniformly distributed between 20 and 21; y for the first x is uniformly distributed between 2 and 3, y for second x is uniformly distributed from 5 to 6) training sets the following weight matrix results:

2.1896	.4704	6.7886	6.7930	10.0029	20.5381
5.1942	8.3097	.3457	.5346	2.0208	5.0894
.0770	3.8342	.6684	4.1749	1.00	1.00

The counts of winners for the neurons is [0, 0, 0, 0, 5001, 4999] showing that the approximate centroids of the cluster in the last two columns of the weight matrix along with the fact that the occurrence is only in those neuronal outputs.

Using this concept with manual control experimental data of disturbance, error and human control as inputs, the control surface of the human operator can be approximated as a series of clusters that correspond to fuzzy rules. These clusters of the control space contain information of the perceptual, cognitive and motor processing of the human operator.

2.2 Fuzzy Inference Systems

Fuzzy inference systems use IF THEN ELSE rules as do conventional AI techniques. Imprecise and incomplete sensory data provided by human sensory modalities to the brain is effectively processed into a perception of the world. With classical set theory the concept of a crisp set is used where there is a distinct and precise boundary. Fuzzy sets have boundaries that are not precise in that the transition from non-membership to membership is gradual rather than abrupt. This gradual change is defined by a membership grade function μ_A

$$\mu_A : X \longrightarrow [0,1].$$

where X is the universal crisp set that is being considered and A is the label of fuzzy set defined. The value of the membership grade is between 0 and 1 thus defining the compatibility to the set in question. The basic feature of fuzzy sets is the lack of sharp distinctions, the ability to capture the vagueness of natural language and measurement uncertainty. The bold trapezoidal shaped function in Figure 5 represents a fuzzy set membership grade. It is important to note that the shapes of the fuzzy functions can be arbitrary and can assume multi-dimension on X_i forming hypershapes. The fuzzy sets shown in Figure 5 represent linguistic terms and ideas associated with negative large, negative medium etc.. This is an important advantage since the system description can be described in a natural manner that is important for investigators that do not have mathematical backgrounds. This a good example of being able to generalize concepts of intervals of real numbers and real numbers to fuzzy intervals and fuzzy numbers. The advantage of the concepts of fuzzy numbers and fuzzy intervals is the ability to express the effect of measurement error more faithfully in a simple linguistic manner which in their own way are vague.

When fuzzy numbers and intervals as defined above represent the state of a system that system is known as a fuzzy system. The necessary steps in defining a fuzzy system include selection of input and output variables, selection of the linguistic states for each variable, selection of linguistic fuzzy inference rules, initial definition of membership grade functions for all linguistic states, initial selection of operations for inference rules and selection of a defuzzification methodology There are a number of fuzzy operators such as multiplication, addition [11] that allows fuzzy relationships to be developed to describe the system. The fuzzy inference rules are called fuzzy associative memories (FAM's) by Kosko [2]. The key part in developing a fuzzy system is to define the fuzzy functions (shape and linguistic label) based on practical experience or the examination of test data. In the past this has been done by a subject matter expert and then tuned based on experimentation. Kosko [2] has suggested that test data can be input to neural networks and the fuzzy rules developed from clustering of patterns in the data. This concept known as neural fuzzy systems eliminates the need for a specific subject matter expert.

3.0 Manual Tracking Experiment

Three basic characteristics have been used by Adams [12] to define the tracking task:

" (1) A paced (i.e. time function) externally programmed input or command signal defines a motor response for the operator, which he performs by manipulating a control mechanism.

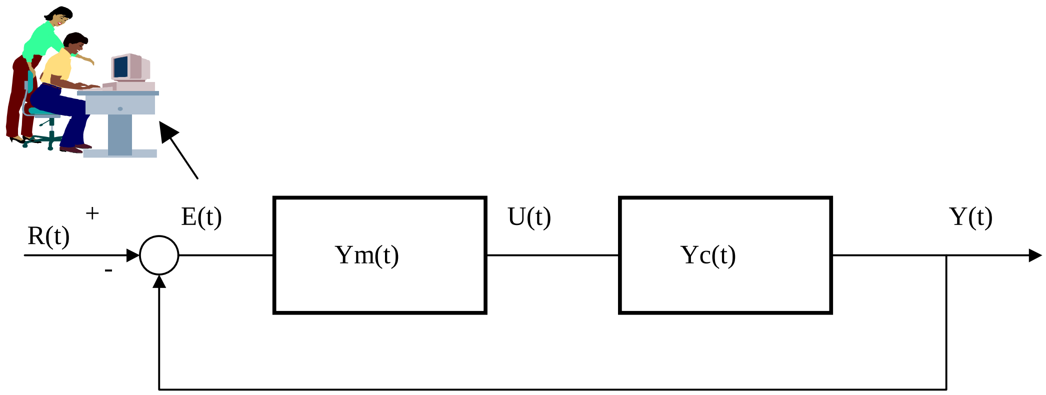
(2) The control mechanism generates an output signal.

(3) The input signal minus the output signal is the tracking error quantity, and the operator's requirement is to null this error. The measure of operator proficiency ordinarily is some function of the time based error quantity."

Although there are many ways to present data of the tracking task to subjects in an experimental setting two are generally used, compensatory and pursuit. In the compensatory task the subject has the error displayed and he attempts to null it to zero as random inputs are presented. On a computer terminal there is a reference mark at the center representing zero error and the moving spot represents the current state of the error. Figure 3 illustrates the closed loop schematic. In pursuit tracking the subject simultaneously observes the track and his own output On a computer terminal the subject would see the randomly moving target spot, the spot he controls and the distance (error) between the two. For both cases the subject uses a mouse or joystick to provide motor control. The tracking task is well suited as a model of everyday tasks such as vehicular control and the control of movements

In the past there has been significant research in manual control which dates back to the 1940's. The demands of the Second World War, however, pressed that a more systematic study of tracking problems be pursued. The urgency of this problem was especially important in air warfare, where targets moved fast and the aiming guns had to be swung correspondingly. Therefore the Second World War saw several studies in this regard [13]. After the war researchers found problems of more general interest. Academic psychologists became interested in the manual control problem with the pioneering work of Craik [14, 15]. Work in the field became very sparse during the late eighties and into the present time.

Tracking studies are theoretically important since a tracking task can be devised that requires almost any degree of visual motor skill from trivial to very difficult. The task can be defined in strictly mathematical sense and measurement of performance to any desired degree of accuracy. Both track and response have been described in terms of information load and closed loop control theory. McRuer [16] used classical control theory and describing functions



where R is a random input, E is the error, U is the manual control, Y is the output, Ym(t) is a representation of the human operator and Yc(t) is the representation of the control

Figure 3 Compensatory Tracking

in the isomorphic model while Baron and Levison [17] used modern optimal control theory that described the human operator. They described the human operator as an optimal estimator of state (Kalman Estimator), linear predictor and a linear quadratic optimal controller to successfully model a tracking task. The problem with these mathematical approaches is the determination of transfer function time constants and statistics of the display and motor noise from psychophysical data. The major difference in the nuero-fuzzy approach is that the optimal and isomorphic approaches started with specific mathematical models. The neuro-fuzzy approach is a data driven representation.

4.0 Fuzzy Model Development

Using ten subjects to collect data for the one-dimensional horizontal compensatory task the fuzzy system model of the human operator is developed. The experiment used a commercial man-machine software package [18]. Each data set contained over 2000 timed data points of disturbance, control input, error and human output. Six data sets were used in the unsupervised training procedure. The other four data sets were used for a validation of the fuzzy system model.

4.1 Compensatory Horizontal 1-D Fuzzy System Model of the Human

After carefully tuning the learning rate for the unsupervised NN learning and starting with random synaptic vectors some significant results were found. There appeared to be little correlation with human control and the disturbance directly. Since the compensatory task requires the subject to null error this is to be expected. When the error and the control were considered a clustering pattern appeared. Figure 4 illustrates the clusters with "+". The clusters represent what makes common sense, when the human operator perceives a large error then the operator will use large control to null that error. The straight line for subject one illustrates that trend. Clustering results from the six subjects in the unsupervised learning were similar. .

As a first guess based on the patterns of the clusters the seven fuzzy sets for both error and human control are considered. Also assume that the sets are all of equal size over the universe of discourse (+- .8) as shown figure 5 for both control and error.

The linguistic labels are defined as follows:

- Human Control Input (R)
    - NL Negative Large
    - NM Negative Medium
    - NS Negative Small
    - NZ Near Zero
    - PS Positive Small

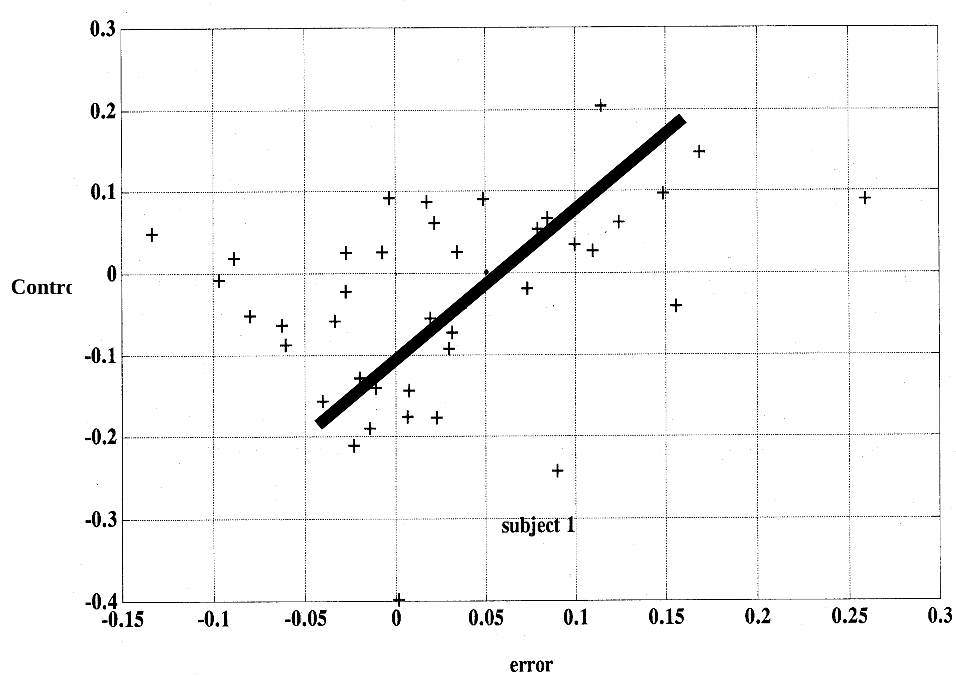


Figure 4 Clustering of Control-input data

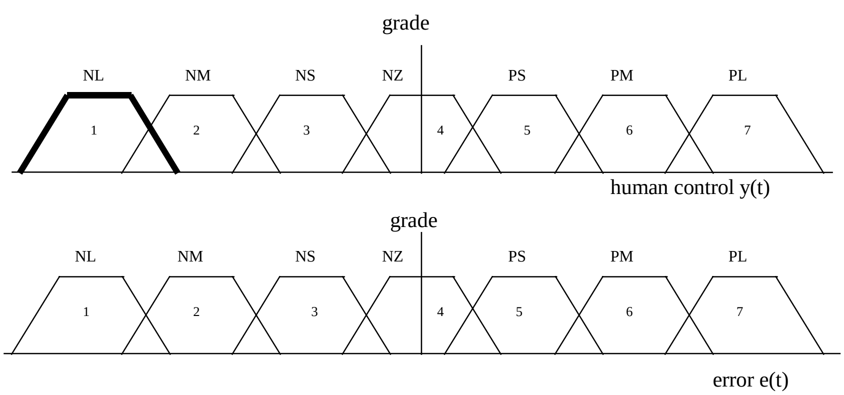


Figure 5 Fuzzy set definition

- PM Positive Medium
- PL Positive Large

* Error (E)
  - NL Negative Large
  - NM Negative Medium
  - NS Negative Small
  - NZ Near Zero
  - PS Positive Small
  - PM Positive Medium
  - PL Positive Large

The human operator in this task will be motivated to null or minimize the error. As a first estimate of that human strategy using these fuzzy sets consider the seven rules as follows:

- IF Error IS Negative Large THEN Human Control is Negative Large
- IF Error IS Negative Medium THEN Human Control is Negative Medium
- IF Error IS Negative Small THEN Human Control is Negative Small
- IF Error IS Near Zero THEN Human Control is Near Zero
- IF Error IS Positive Small THEN Human Control is Positive Small
- IF Error IS Positive Medium THEN Human Control is Positive Medium
- IF Error IS Positive Large THEN Human Control is Positive Large

Note here that it would seen that in order to null large negative error the operator would use positive large. The polarity of the joystick is negative that results in the fuzzy inference rules we have shown above.

Input to the fuzzy system is the random disturbance that the human subject also experiences. This signal would be R(t) in the Figure 3 block diagram. The random signal input is generated by the sum of several sinusoidal signals for this data set. There are nine separate sinusoids with the corresponding nine frequencies and relative amplitudes. Maximum amplitude is .33 for this test case. The controller that the human subject is controlling is a first order system (1/s) with no delay and an open loop gain of 10.

The Fuzzy System Toolbox [19] with MATLAB is used to generate the fuzzy model. The function FRULES evaluates sets of fuzzy rules defined by these fuzzy shapes. The function uses R rules (seven in this case) to determine an M element output vector (one here for modeled human control) given an N element input vector X (one for E(s)). The R rules are defined with an antecedent matrix A(this case A is [1 2 3 4 5 6 7]') and a consequence matrix C (in this case C is [1 2 3 4 5 6 7]') which correspond to the seven fuzzy rules listed above. Each ith row of the antecedent matrix A indicates the conditions for which that rule applies. Each such row contains N values where the jth value indicates which fuzzy set of the jth input is active or contributes. Each corresponding ith row of the consequence table C determines the result if the ith rule applies. Each row has M values indicating which fuzzy set the output variables should be part of their associated universes of discourse.

An example of this process will illustrate the application of fuzzy logic to the model. Consider the fuzzy overlapping sets similar to the above human operator model with an error signal of .1 as shown by the dotted line in Figure 6. At this value the membership grades are .75 for error PS and .25 for error NZ. The fuzzy associative rules that then apply are

- IF Error IS NearZero THEN Human Control is Zero
- IF Error IS Positive Small THEN Human Control is Positive Small

Each fuzzy rule of the consequence that applies is then scaled by the membership grade of the associated antecedent resulting in the fuzzy rules result that is another fuzzy set. If there were multiple antecedents that were ANDED then the fuzzy AND operator (MIN (Antecedent 1, Antecedent 2)) would be applied as illustrated in Kosco [2]. In order to get a single value for the human model control the resulting fuzzy set must be defuzzified. One technique that is usually applied is to determine the centroid of the fuzzy set resulting from the rules application.

The centroid of the fuzzy rules application is the simple area centroid of two trapezoids. Using the vertical axis in Figure 6 as a reference the defuzzified value of human control y is:

$$y= (A1*x1+A2*x2)/ (A1+A2)$$

where x1 and x2 are the positions of the area centroid of A1 and A2 relative to the vertical axis

or

$$y= (.225*.5*.15+.375*.25*.075)/(.225*.5+.375*.25) = .116.$$

5.0 Results

By constructing the fuzzy system described by the seven fuzzy rules and stimulating that model with the actual error signal the result is a modeled human control. Those two outputs are then plotted together in Figure 7. It appears that the modeled input actually leads the real human operator by a small amount. This

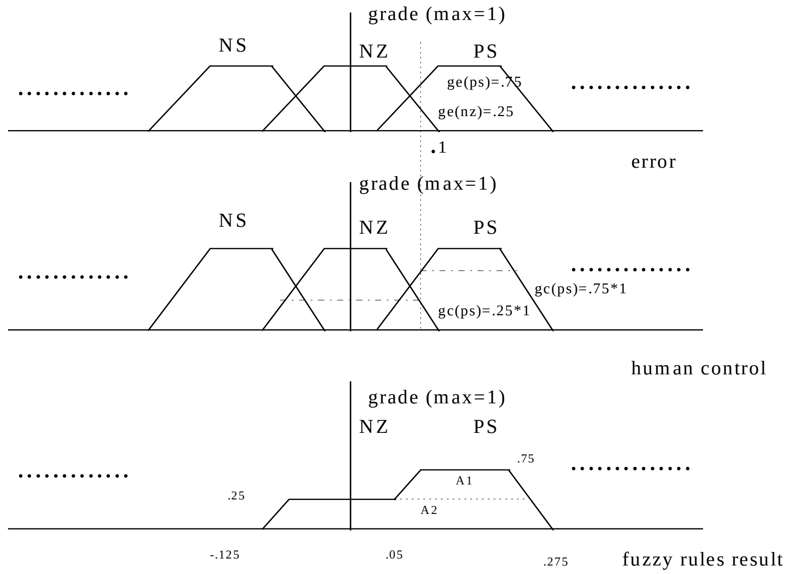


Figure 6 Fuzzy System Example

is due to the fact that the fuzzy model does not allow for the human delay that results from the perceptual, cognitive and motor processing. That delay would be of the order of 50 milliseconds.. By shifting the model output by 2.5 seconds there is close correspondence in phase over the entire time span. It seems that the additional delay is due to processing in the computer in developing the display associated with the compensatory task. This delay was found to be consistent over six other human subjects that were tested.

Due to the use of five equal fuzzy sets small errors do not correspond well in the model. Using smaller sets near the zero point as well as more rules in that area should improve that response. There is a good correspondence in regard to larger amplitudes although some of the modeled controls are clipped.

6.0 Conclusions

This initial research indicates that neuro-fuzzy systems can be used to generate a model of human behavior. Our specific case involves the manual control task that would be common for simulated aircraft control for CGF. The use of simple uniform membership grades for the fuzzy inference system resulted in good correlation with actual subjects. Further optimization of the membership grades should improve the model performance further. Further research will include modeling the pursuit task which will depend on disturbance as well as error thus resulting in a two dimensional fuzzy system.

Although the compensatory task is a one dimensional model, the use of NN's gave insight into the membership grade structure. With this case one could almost conclude the NN results from common sense and experience. For multi dimension solution space the visualization of hyperspace membership functions are complex and the NN clustering is an important tool in developing behavioral models. A further application of the compensatory model will be to drive them with aircraft simulator data of the glide slope task. The output of the model of the human will then be compared to the actual man in the loop simulator response. Neuro-fuzzy systems

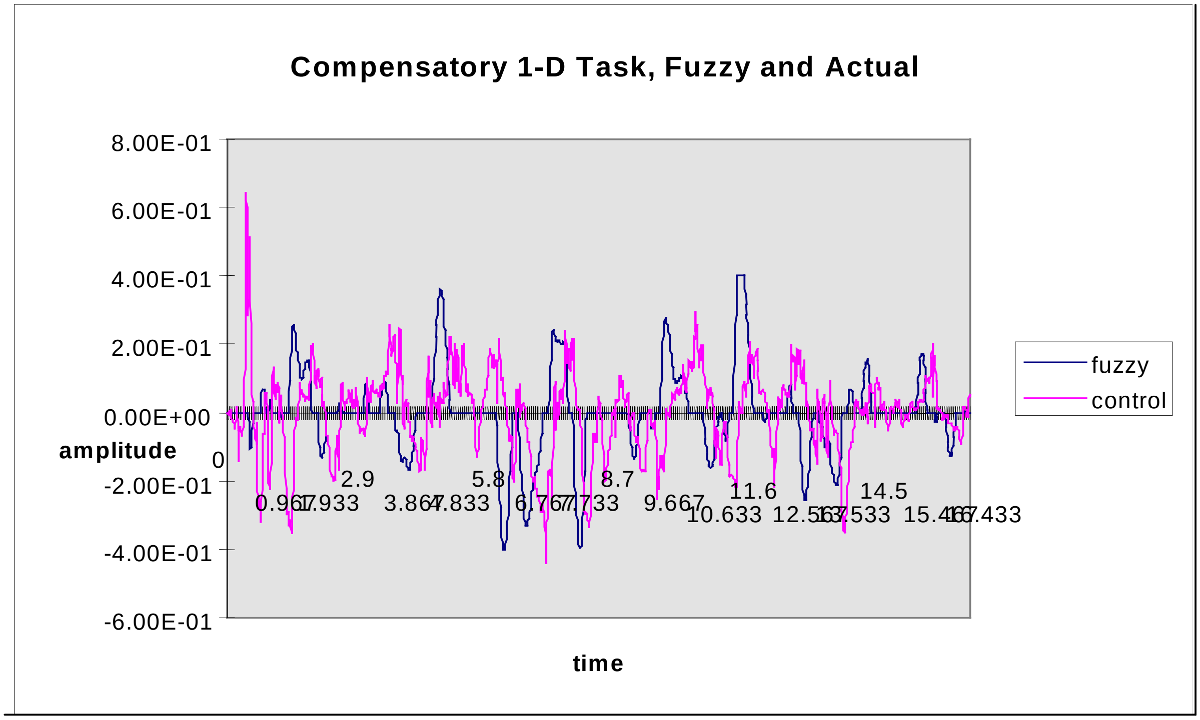


Figure 7Comparison of Fuzzy Model and Actual Human Operator

are a new tool in the behavioral representation toolbox and can be a significant part of other hybrid systems that may include classical AI and planning theory to construct realistic synthetic battlespaces of the future.

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Acknowledgements

A special acknowledgement to all the students and friends that participated in the manual control experiment. Their interest in this research is much appreciated.

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