Fuzzification using Approximation with Fuzzy Controllers to Extract Structure and Motion Environments in Dynamic Humanoid Robotic System from the Opted and Forced Uncertainty by Quantization in Nonmonotone Neural Networks.

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Abstract

Fuzzy controllers are special expert systems .Each employs a knowledge base,expressed in terms of relevant fuzzy inference rules, and an appropriate inference engine to solve this control problem which vary substantially according to the nature of the control problems in this research the control problem is a complex task in this robotics research which require a multitude of coordinated actions such a s maintaining a prescribed state of single variable ,which are capable of utilizing knowledge elicited from human operators extended to dynamic robotic system with nonmonotone neural networks.

Keywords - Fuzzification, Fuzzy controllers, Expert System, Fuzzy sets, Quantization, Nonmonotone, Dynamic Robotic system

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1. INTRODUCTION

In this research it has been observed that experienced results are able to perform and recognized that the areas of fuzzy systems and neural networks are strongly interconnected, Here in this research neural networks have been proven Fuzzification very useful in this Humanoid Robotic research using fuzzy set for constructing membership functions of relevant fuzzy sets and other context dependent entities from sample data. We had explored, Here the motivation for approximating fuzzy systems by neural networks is based upon the inherent capability of neural networks .This is relevant to fuzzy controllers and more for fuzzy expert systems that processed large numbers of fuzzy inference rules in this real time research. The concept of information is intimately connected with the concept of uncertainty. The most fundamental aspect of this connection is that uncertainty involved in any problem-solving situation is a result of some information deficiency , Information pertaining to the model within which the situation is conceptualized may be incomplete,imprecise,fragmentary,not fully reliable,vague ,contradictory ,or deficient, In this research we measured the uncertainty involved in a problem solving situation in forced uncertainty by quantization in Nonmonotone conceptualized in a particular methodology in fuzzy controllers to extract structure and motion environments. This is crucial in control problems for which it is difficult or even impossible to construct precise mathematical models, or for which the acquired models are difficult or

expensive to use. These difficulties results from inherent nonlinearities.

2. Problem definition

In the above perspective the traditional techniques of system [1,2,3,4,5] analysis are not well suited for dealing with humanistic systems because they fail to come to grips with the reality of the fuzziness of human thinking and behavior, [6]. Thus to deal with such systems radically, we need approaches which do not make a fetish of precision, rigor and mathematical formalism, and which employ instead a methodological framework [7], which is tolerant of imprecision and partial truths [8].

3. Proposed Research

The area of fuzzy systems has chosen in this research in the area of fuzzy control, it is thus appropriate to research in fuzzy control Fig (1). Our research in fuzzy control includes a connection between fuzzy controllers and neural networks; also we worked in the issue of fuzzifying neural networks from Dynamic Robotic System from the opted and forced uncertainty.

3.1.1. Fuzzy Classifications

Here the 8 linguistic states are distinguished for each variable, represented by triangular – shape fuzzy numbers equally spread over the range of values the variable have the same range[-7,7] which is the range[-a,a]
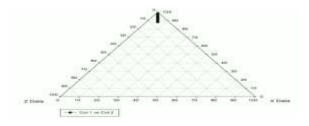

Fig 1. Fuzzy values plotted for various neural weights and neural schemas

3.1.2. Fuzzy Algorithm

In this research in the design of fuzzy controllers and the analysis of them by the below control logic are The relevant input and output variable of the Humanoid Robotic controller Fig (2) and ranges of their values selected linguistic states [9,10,11] for each variable and express by appropriate fuzzy sets.
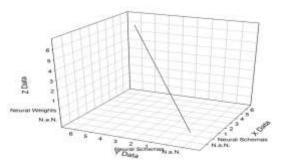

Fig 2. Fuzzy membership functions on Neural Schema with Neural Weight

A fuzzification function f_e applied to a variable e. and made the fuzzification form f_e:[-a,a]→ R fig (2).Where R denotes the set of all fuzzy numbers and $f_e(x_0)$ is a fuzzy number chosen by f_e as a fuzzy approximation of the measurement e= x_0,the fuzzy set $f_e(x_0)$ enters into the inference process [12,13].This control problem is formulated in terms of a set of fuzzy inference rules, here it has a canonical form [14.15]. If e=A and $\dot{e}$=B, then v=C Fig (3) fuzzy sets representing the linguistic states of variables e, $\dot{e}$,v, respectively and made reasonable to define a degree of relevance of the rule based by eqn $i_1[i_2(A(x_k),B(y_k)),C(z_k)]$, where i_1, i_2 are t-norms and the measurement of input.

4. Fuzzyfying the Backpropagation learning algorithm in neurons

In this research all real numbers that characterize a classical neural network become fuzzy numbers in its fuzzified

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counterpart. Inputs to network and outputs of neural at hidden layers O $O N_k$,of a neuron then the inputs $X_{K0} X_{K1}, \dots, X_{Kn}$, the weights $W_0, W_1, \dots, W_n$, and the output Y_k of this neuron are all fuzzy numbers. The output of each neuron, exemplified here by the neuron is given ineqn. $Y_K = S_\beta(\sum_{j=0}^n W_j X_{kj})$, Where S_β is a sigmoidal function for the chosen value of fig (3), the steepness parameters $\beta, W_j X_{kj}$ is the designate fuzzy number and the sum is $A_k = \sum_{j=0}^n W_j X_{kj}$ are calculated by fuzzy arithmetic and the output of the neuron obtained is determined by using the extension principle, Error function E_p, is employed in Fig 4.
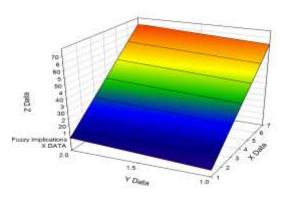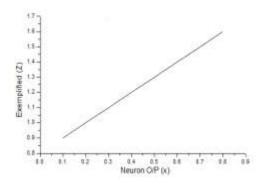

Fig. 3 Fuzzy implications

Fig.4 Nonmonotone Neuron Exemplified

Our back propagation learning algorithm n a fuzzy network   with m outputs for each training sample p Fig(5) ,is defined by the eqn.

$$E_p = \frac{1}{2}\sum_n (T_k^p - Y_k^p)^2$$

$$\lambda = \frac{1}{2}\sum_{k=1} (t_{k_2}^p - t_{k_1}^p)^2$$

With their fuzzy counterparts and applying fuzzy arithmetic.

5. Outcome - Fuzzifications of classical dynamic systems

U is a set of time functions, u : T → X , which is required to be closed under a composition Fig (5) that is called a τ-concatenation and implemented as follows: for any u,v ϵ U and τ ϵ T, the τ-concatenation, $u0_\tau$ v , is the function fig 4. S is a global state-transition functions: T x T x Z x U → Z,which is required to have the following properties'(t,t,z,u) = z (consistency);s(t_3,t_1,z,u) = s[t_3t_2, $s(t_2, t_1$,z,u),u] for any $t_1 \le t_2 \le t_3$(state-substitution property);s(t_2,t_1,z,u) = s[t_2t_1,z,v) when u(t) = v(t) for $t_1 \le t \le t_2$ (causality);r is a response function used in r: T x Z x A → B,. One way of fuzzifying these systems is done Fig (5), by using linguistic approximation from datas in the Neural Schema and Neural weights for different Humanoid Robot complexities.
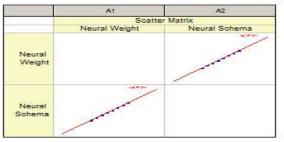

Fig. 5 Derived approximation as nonmonotone and Neural Weight V/S Neural Schema computational equivalence.
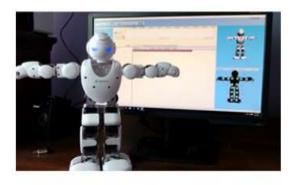
6. Results and Discussions

In this research the following are the results achieved in computational equivalence between continuous functions, neural networks, and fuzzy expert systems each neuron,provided that the range of input variable is discretized into n values and the range of the output variable is discretized into m values of Humanoid Robotic System Fuzzification.

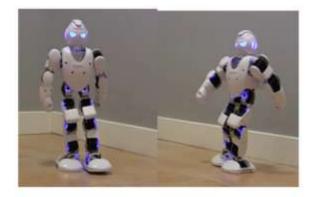## 7. Experimental Validation for fuzzy inference

Fuzzy input-output controllers, that is fuzzy expert systems based on multiconditional approximate reasoning and a defuzzification of obtained conclusions are universal approximates. Humanoid Robotic Neural networks with n inputs , m outputs(n≥1,m≥1), one hidden layer and a continuous activation function in the sigmoid function in each neuron are universal approximates as given in the figures of humanoid robotic system in the experimental platform.

8. Conclusion

In this research in approximate linguistic terms is efficient, thus the role of uncertainty in reducing complexity is well characterized, an alternative approach is also developed on the premise that the key elements in human thinking are not numbers, but labels of fuzzy sets. Thus logic with fuzzy truths, Humanoid Robotic fuzzy connectives and fuzzy rules of inference is obtained for Dynamic Robotic System from the opted and forced uncertainty by quantization in Nonmonotone neural networks executes as gentle walk, walking backwards towards wall, sensing and trajectory towards right and left locomotion.

Comparisons of simulation Vs experimental platform (output experimental values are plotted as fuzzy values)

Gentle walk   Walking backwards towards wall

Walking towards right   Walking towards left

9. Future work

Another way is to apply the extension principle directly to the differential equations involved, this requires in some sense the development of a fuzzy differential calculus. Also can show how a proper defuzzification method can be determined by Humanoid Robotic learning algorithms, an interesting strategy for dealing with the defuzzification problem based on sensitivity analysis by applying the predictions.

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