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A Correlation among Potential Fields, Dempster-Shafer, Fuzzy Logic and Neural Networks Based Intelligent Control Systems

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***Abstract* – The main object of the research work is to compare and correlate the Intelligent control which has a class of control technique used in several artificial intelligence computing approaches namely Motion or Path Planning (using potential fields),Evidence Theory (dempster – shafer),Fuzzy Systems, Neural Networks etc. A detailed study to arrive a research based solutions to find relations among these intelligent control techniques namely – potential fields used in motion or path planning of robots, the theory of evidence, fuzzy systems and neural networks has been achieved. This paper attempts to correlate the intelligent control technique based on real time applications and results has been achieved.**

***Keywords* – Intelligent control, dempster – shafer, potential fields, fuzzy systems, artificial neural networks.**

I. Introduction

Intelligent control techniques are used in several applications. They are of great interest to engineers and researchers across various disciplines. Intelligence in this context mainly means less user interactions and automated adaptation to changing environments. Over the years various control schemes have been proposed, some have been adopted by the industry others are still in experimentation [1].

The focus of this paper is to address relations among some of these intelligent control techniques such as potential fields, fuzzy systems, dempster – shafer and artificial neural networks. This relation is discussed in section 3. Before discussing about how they relate to each other, it is important to have a background on these topics. A brief overview of each of these techniques is presented in section 2.

Depending on the application, some of the intelligent control techniques can be perhaps combined together to form a much better reliable and predictive system. For instance, it is easy to note that, dempster – shafer, fuzzy systems and artificial neural networks are theories that address vague and uncertain information.

II. Intelligent Control Techniques – A Review

A. Potential fields.

Potential field is a popular concept used in motion or path planning of robots. The idea is that the robots do not collide with each other, avoid obstacles and finally reach the specified target. One of the ways this can be implemented is by making the robots repel away from the obstacles, attract towards each other if they are far and repel if they are too close to each other. Finally, they are attracted towards the target. The robots move towards the target as a result of the total forces acting upon them which are determined by the sum of the potential fields at any point in the path.

$$\text{Potential field, } V(x) = \sum_{i=1}^{N} k_i V_i(x)$$

with $V_i(x)$ the individual potential fields from the i-th obstacle/target, N the number of obstacles plus targets, and ki some relative strength weighting coefficients [3].

B. Dempster – Shafer.

Dempster – Shafer is a theory of evidence which deals with belief and plausibility by combining separate pieces of information (evidence) to calculate the probability of an event. According to this theory, there can be two kinds of uncertainty:

- System can behave in random ways. This is similar to the Bayesian theory.

- Uncertainty is subjective, it deals with ignorance.

$$m_{12}(A) = \frac{\sum_{B \cap C \subset A} m_1(A) m_2(B)}{\sum_{B \cap C = \phi} m_1(A) m_2(B)}$$

This formula represents combination evidence from two witnesses, where with ϕ the empty set and mi(A) the basic probability assignment of set A according to witness I [3].

Consider a situation where there are 2 witnesses giving information about the number of cars parked in a parking lot. The total number of cars in the parking lot is known to be 100. Witness #1 says there are 20 cars of type A, 60 cars of type C and the rest he did not count. Witness #2 says there are 20 cars of type A, 60 cars of type either A or C and the rest he did not count.

TABLE 1.CALCULATION OF BELIEF AND PLAUSIBILITY.

	m1(A)	**m1(C)**	**m1(θ)**	
	0.2	**0.6**	**0.2**	**1**
m2(A) 0.2	0.04	0.12	0.04	0.2
m2(A C) 0.2	0.04	0.12	0.04	0.2
m2(θ) 0.6	0.12	0.36	0.12	0.6
1	0.2	0.6	0.2	1

TABLE 2.CALCULATION OF K

	m1(A)	**m1(θ)**		K =	0.12
	0.2	**0.2**	**1**	m12(A) =	0.27
Bel (A) =	0.27	**Pl (A) =**	0.45	m12(C) =	0.54
Bel (C) =	0.54	**Pl (C) =**	0.72	m12(AC) =	0.04
Bel (AC) =	0.86	**Pl (AC) =**	1	m12(θ) =	0.13

It is seen that from the account of witnesses it can inferred that there are no less than 27 cars and no greater than 45 cars for type A. The same can inferred for car C and AC [3].

C. Fuzzy Systems.

Fuzzy logic emphasizes on practical knowledge into real life solutions. Fuzzy logic evolved as a key technology for developing the knowledge based systems (KBS) in the control engineering to incorporate practical knowledge for designing controllers. It tries to balance the question of precision. Fuzzy logic tries to answer, should a rough practical answer be more effective than a complex precision [4]. Equation of a fuzzy system is given as:

$$u(x) = \frac{\sum_{i=1}^{N} z_i \prod_{j=1}^{n} \mu_{ij}(x_j)}{\sum_{i=1}^{N} \prod_{j=1}^{n} \mu_{ij}(x_j)},$$

This formula uses product inferencing, centroid defuzzification, and singleton control MFs. There are N rules and n state components xj, zi are the control representative values, and $\mu_{ij}(x_j)$ is the MF for state component j in rule I [3].

Steps involved to develop a fuzzy system are:

a. Normalization – Mapping physical values to normalized (scaled) universe of discourse.
b. Fuzzification – Converts the crisp input values to linguistic variables as defined by the membership functions.
c. Inferencing – Combing the fuzzy rules to govern the system operation.
d. Defuzzification – Converts the fuzzy values back to crisp values.
e. Denormalization – Scale transformation to map the normalized values back to the actual, physical values [4].

Following is an output of a fuzzy controller, with system input u(t) as the output of the controller. The controller has two inputs one the error e(t) and the derivative edot(t).

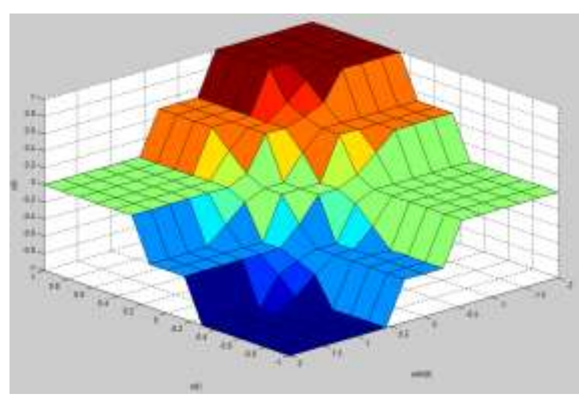

Fig 1(a). Surface view of the output surface of the Fuzzy System.

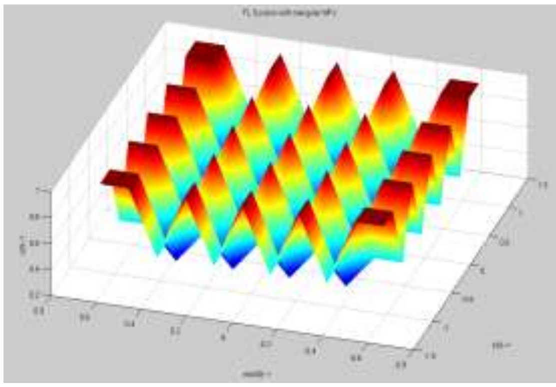

Fig 1(b). Fuzzy logic system with triangular membership functions

D. Artificial Neural Network (ANN)

Artificial neural network operates on the principle of largely interconnected simple elements called neurons operating as a network function. A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between elements. Neural networks are adjusted or trained so that a particular input leads to a specific target output. The main aim of the network is to find suitable weights to minimize the error between the desired output (target) and the actual output from the artificial neural network. The equation for the ith output of a neural network is

$$u_i(x) = \sum_{j=0}^{N} w_{ik}\phi_k\left(\sum_{j=0}^{n} v_{kj}x_j\right)$$

with n state components xj, x0=1 a threshold offset, N hidden layer units, vkj the input layer weights, wik the output layer weights. The activation functions are $\phi_k(.)$, which can be nonlinear functions such as sigmoids, tanh, radial basis functions (Gaussian), etc [3].

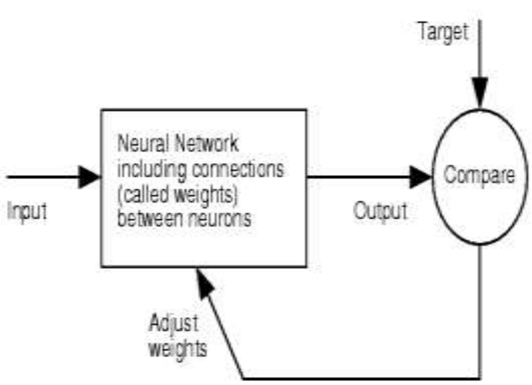

Fig 2. Simple block diagram of a neural network [5].

III. Relation Among Intelligent Control Techniques

There are several methods how we can correlate these techniques with each other. This paper uses certain observed methods which can be used to relate them:

i. Presenting a comparison table among some of these intelligent control techniques.
ii. Observing equations and finding similarities.
iii. Theories or articles proposed on how some of these techniques are related or can be used in conjunction with each other.

A. Comparison of various intelligent control techniques

The goal artificial intelligence tries to mimic human intelligence. Each of these intelligent techniques tries to address some aspect of human intelligence.

i. Fuzzy Logic – Linguistic communication among humans.
ii. Artificial Neural Networks – Tries to mimic biological neural structure of humans.
iii. Dempster – Shafer – Deals with ignorance or lack of knowledge.
iv. Potential Fields – To mimic our response to physical objects.

TABLE 2. COMPARISION OF BASIC METHODS IN COMPUTATIONAL INTELLIGENCE.

Kind of Knowledge	**Method**	**Advantages**	**Disadvantage**
Data Based, Supervised, Unsupervised, Reinforcement	Perceptron Networks or Feed forward neural networks	Robust against input uncertainties.	Topology hard to define.
			High training effort.
		Fast after training.	Process knowledge not extractable from the trained network.
	Evolutionary Neural Networks	Same as for perceptron networks.	Same as for perceptron networks.
		Topology optimization included in method.	Very high training effort.
Process Knowledge Based (process relations)	Fuzzy Systems	User friendly, transparent knowledge representation.	No security against implementation of wrong process knowledge.
		Robustness.	Validation and tuning after basic design.

Data and Process knowledge based, supervised (input and output datasets and proess relations)	Neuro-Fuzzy Systems	Same as for fuzzy and perceptron networks. Validation and tuning implemented method.	Same as for fuzzy and perceptron networks.
All kinds of knowledge	Evidence theory (Dempster-Shafer)	Very flexible applicability	Reasoning scheme must be designed for each problem approximately

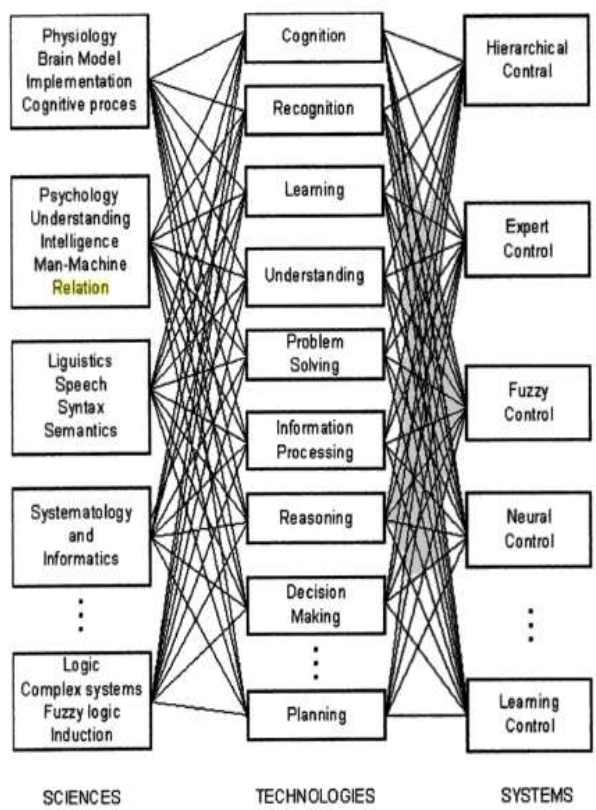

Fig 3. Relationship among intelligent control systems[11].

B. Observing equations and finding similarities.

There are several similarities that can be drawn from equations of intelligent control techniques. Although collectively there may not be a similarity, different combinations of these techniques bring about different similarities. Some of these are:

a. Potential fields, fuzzy logic and neural networks have weights in their equation. From the equation of potential fields it can be seen that k_i is the relative strength weighting coefficients. In fuzzy logic systems, the centroid z_i, is weight. For neural networks – v_{kj} , w_{ik} are the input layer weights and the output layer weights respectively.

b. Similarly, it can be seen that from the equation of potential fields, fuzzy logic and neural networks, N represents the number of obstacles, rules and hidden layers respectively. Therefore the size of N for each of these techniques determines the amount of computation time required to execute.

c. Comparing equations of dempster – shafer and fuzzy logic, it is observed that both of them are normalized. Perhaps only an intuitive relation can be found to compare dempster – shafer and the rest of the three techniques. This is because the summation constraint for dempster – shafer is different from the rest of the techniques.

d. Comparing equations of artificial neural networks and potential field, it can be concluded that the potential field equation is a special case of artificial neural network. There are two ways how they can be related:

i. Potential Field in terms of ANN:
Equation for ANN,

$$u_i(x) = \sum_{i=0}^{N} w_{ik} \phi \left(\sum_{j=0}^{n} v_{kj} x_j\right)$$

Equation for Potential field (in terms of ANN),

$$V(x) = u_i(x) = \sum_{i=0}^{N} w_{ik} \phi \left(\sum_{j=0}^{n} v_{kj} x_j\right)$$

where n = 0, $w_{i0} = 0, v_{k0} = 1$ and $x_0 = 1$;

$$V(x) = u_i(x) = \sum_{i=0}^{N} w_{ik} \phi$$

Thus, potential field,

$$V(x) = u_i(x) = \sum_{i=0}^{N} w_{ik} \phi \left(\sum_{j=0}^{0} v_{kj} x_j\right)$$

$$= \sum_{i=1}^{N} w_{ik} \phi$$

This is similar to the actual potential field equation:

$$V(x) = \sum_{i=1}^{N} k_i V_i(x)$$

ii. ANN in terms of potential field:
Equation of potential field,

$$V(x) = \sum_{i=1}^{N} k_i V_i(x)$$

Equation for ANN,

$$u_i(x) = \sum_{i=0}^{N} w_{ik} \phi \left(\sum_{j=0}^{n} v_{kj} x_j\right)$$

Alternatively this can be written as,

$$u_i(x) = V_1(x) V_2(x)$$

This can be explained with the following matlab plot:

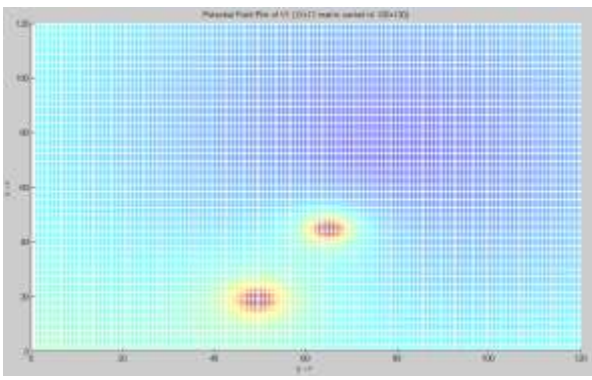

Fig 4a. 2D Plot of Potential V1

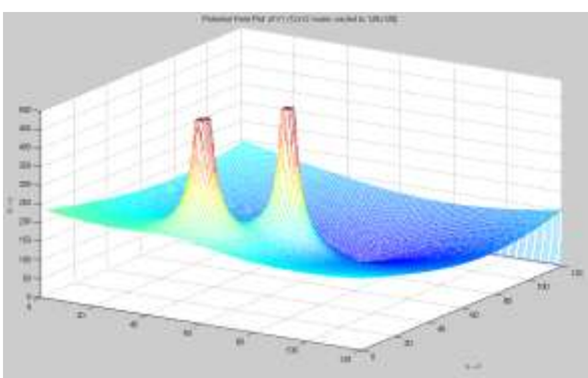

Fig 4b. 3D Plot of Potential V1

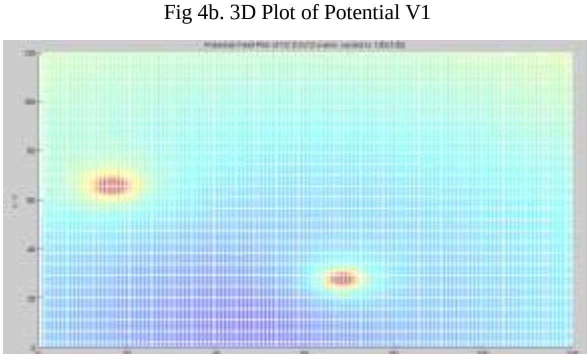

Fig 5a. 2D Plot of Potential V2

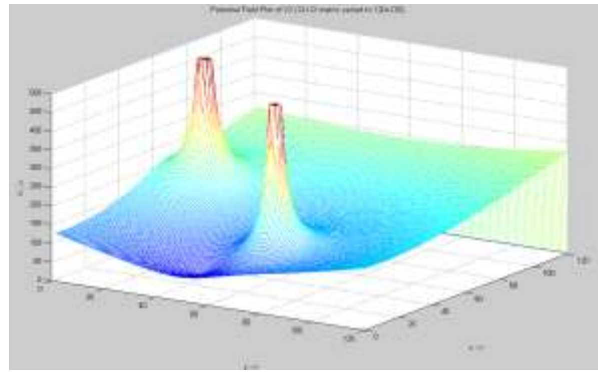

Fig 5b. 3D Plot of Potential V2

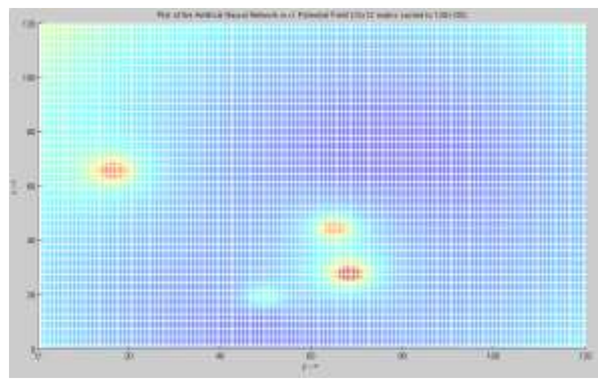

Fig 6a. 2D Plot of Potential V3= V1xV2

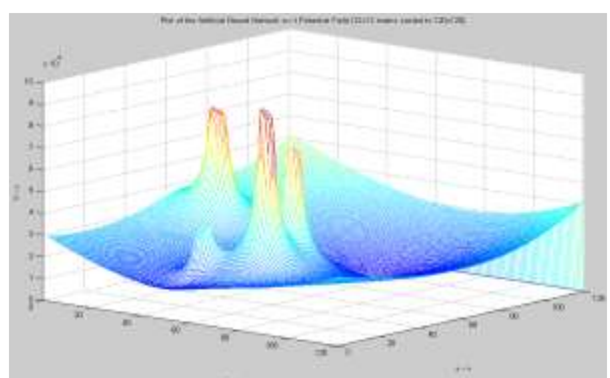

Fig 6b. 3D Plot of Potential V3= V1xV2

Note that in this program the location of obstacles and target in the potential field is chosen at random. Fig 5a and 5b shows a multiplied output of the potential fields $V_1(x)$ and $V_2(x)$. Relating this to ANN equation $V_1(x)$ is the potential field plot of the hidden layer and $V_2(x)$ is the potential field plot of the input layer. Since $V_1(x)$ has 2 obstacles and 1 target, there are 3 hidden layers for the ANN. Similarly, since $V_2(x)$ has 2 obstacles and 1 target, there are 3 hidden layers for the

ANN. The final plot in Fig 5a and 5b has 4 obstacles and 2 targets, the ANN would have a total of 6 layers. The height or depth of the target denotes the weights of the layers in ANN. Thus it can be seen that ANN can be visualized in terms of potential fields.

e. Fuzzy logic and Potential fields are the same if n = 1 and no normalization is used. This can be explained as follows:
Equation for fuzzy logic:

$$u(x)= \frac{\sum_{i=1}^{N} z_i \prod_{j=1}^{n} u_{ij}(x_j)}{\sum_{i=1}^{N} \prod_{j=1}^{n} u_{ij}(x_j)}$$

If this equation is not normalized then:

$$u(x) = \sum_{i=1}^{N} z_i \prod_{j=1}^{1} u_{ij}(x_j)$$

This equation is similar to the potential field equation:

$$V(x) = \sum_{i=1}^{N} k_i V_i(x)$$

Therefore, fuzzy logic is an unnormalized potential field.

C. Theories proposed on relations among these techniques

In this section an attempt is made to relate some of the techniques mentioned above.

i. Generalization of fuzzy set theory to dempster – shafer

Generalizing fuzzy set theory to dempster – shafer addresses the issue of managing imprecise and vague information in evidential reasoning by combining the D-S theory with the fuzzy set theory. In the example provided for dempster – shafer in section 2.2, the numbers of cars counted by the witnesses were in crisp values and the solution to the problem was also in crisp values. What if the witnesses did not count the cars instead just the presented the values in linguistic terms such as – there were “less” cars of type A and the number of cars of type C in the parking lot was “high”. The number of cars reported by the witnesses is fuzzy; hence the solution for this dempster – shafer problem will also be fuzzy. Several papers have been written on how to use dempster – shafer theory to deal with vague information [7]-[10], however, they have not been able to preserve an important principle in dempster – shafer theory, that the belief and the plausibility measures are lower and upper probabilities. In [8], this issue is overcome.

ii. Neural Networks and Fuzzy Systems

A neuro-fuzzy system is a fuzzy system that uses a learning algorithm derived from or inspired by neural network theory to determine its parameters (fuzzy sets and fuzzy rules) by processing data samples. Here neural networks are introduced in a fuzzy system to form neural-fuzzy systems.

This can be better explained with the following example. Consider the function $\sin(10x)\sin(10y)$:

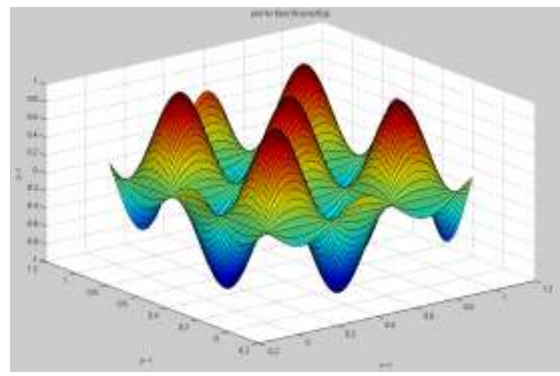

Fig 7. Plot of $\sin(10x)\sin(10y)$

The task here is to train the neural network by providing it some amount of data and to obtain an approximate plot of this function. Adaptive Neuro – Fuzzy Inference System (ANFIS) algorithm is used. This can be implemented using the Matlab anfisedit GUI. In the first case only 10 pairs of data (x,y) is taken.

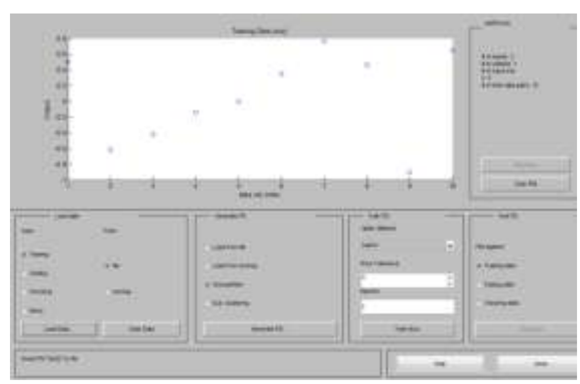

Fig 8. ANFIS editor data loaded with only 10 pairs.

Input:
Number of MFs = 4
MF Type = gaussmf
Output:
MF Type = linear
Error Tolerance = 0.01
Epochs = 30

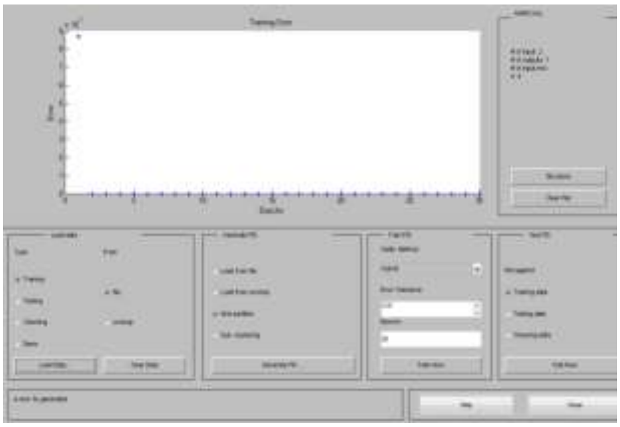

Fig 9. Trained data with specs as mentioned above.

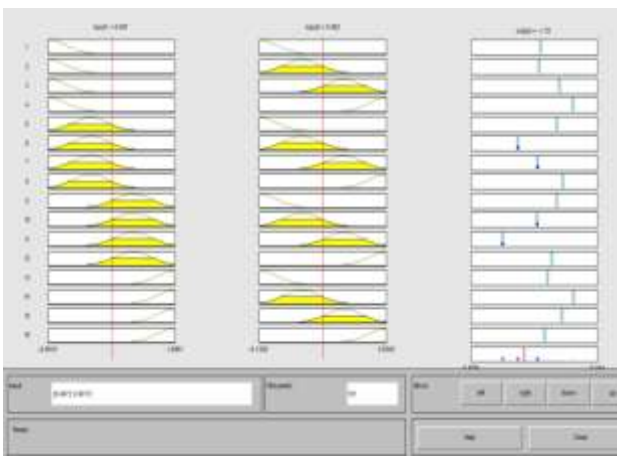

Fig 10. ANFIS Rule Viewer.

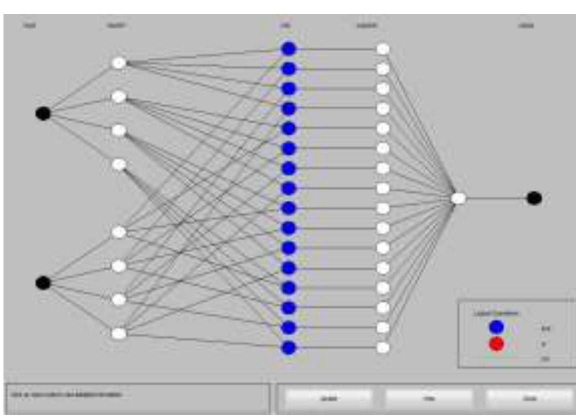

Fig 11. ANFIS model structure.

Here the fuzzy rule base is generated with the help of the neural network.

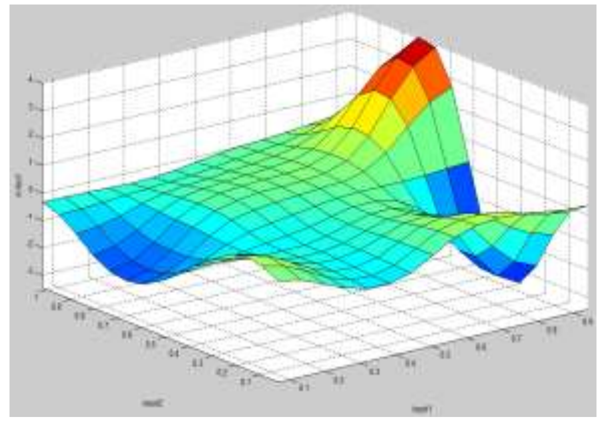

Fig 12. Surface View for 10 pairs of data.

Now, changing the number of MFs in input to 6.

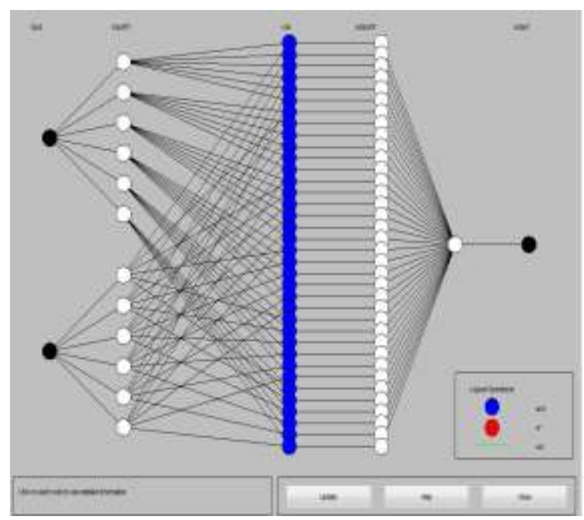

Fig 13. ANFIS model structure.

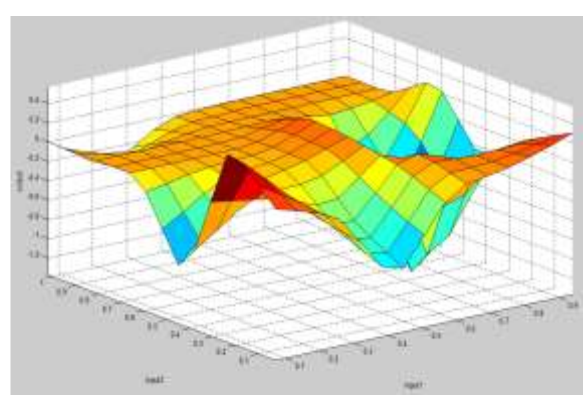

Fig 14. Surface View

It can be seen that the as the number of MFs at the input has increased the number of rules and the number of neurons has increased. Also, from surface view Fig 11 and 13, the function is not similar to the desired plot.

In the second case, the number of data pairs is increased to 100 and following specs are used -
Input:
Number of MFs = 6
MF Type = gaussmf
Output:
MF Type = linear
Error Tolerance = 0.01
Epochs = 30

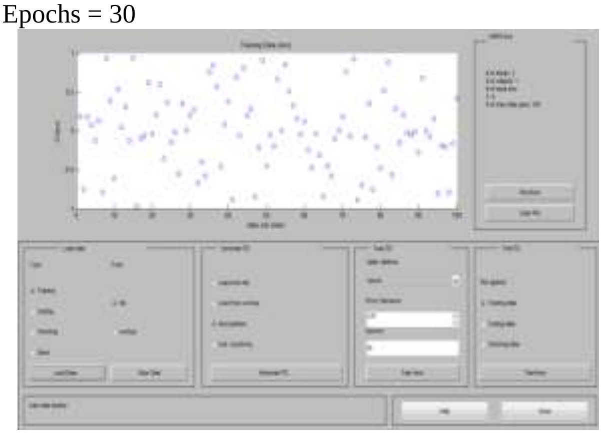

Fig 15. ANFIS editor data loaded with 100 pairs.

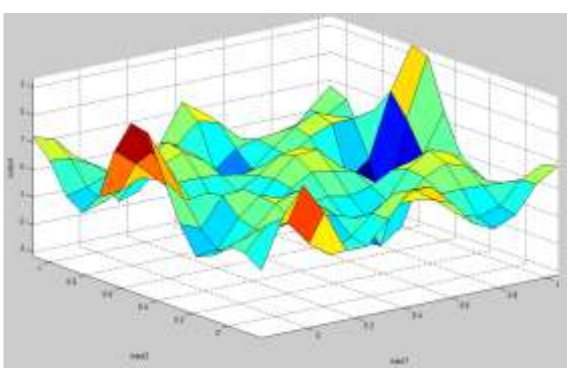

Fig 16. Surface View

This is a much better approximation of the desired function plot.

Another way of relating the two would be by introducing fuzzy systems in conventional neural networks. Thus it could have fuzzy inputs, weights, aggregation, activation functions and outputs. This would convert the standard mathematical models for neurons to fuzzy neurons to form fuzzy-neural systems [12].

iii. Application of neural networks, fuzzy logic and potential fields in navigation of a car

In [13], neural networks, fuzzy and potential fields are used to help park a car in a parking lot. A hybrid navigation structure for a parking problem is proposed with the following elements:

i. Harmonic potential field – The initial path is calculated using potential field. All obstacles (parking slots as well as cars) are considered as static. The path is described as series of orientation marks.
ii. Neural network – It is used as a controller (with back-propagation learning) trying to control the robot to pass through the orientation marks.
iii. Fuzzy controller – A Mamdani type controller is used to solve the problem, if another car starts to move (dynamic obstacle). Then it will take over the control from the neural network and perform obstacle avoidance trying again to find orientation marks.

IV. Conclusion

In this research paper a complete review on the various important intelligent control techniques has been achieved. Possible relationships among these techniques were discussed with suitable applications. This comparison study may be extended to mission critical applications and suitable intelligent techniques adaptation can be achieved.

References

[1]. http://en.wikipedia.org/wiki/Intelligent_control.
[2]. C.Rehtanz, "Autonomous Systems and Intelligent Agents in Power System Control and Operation", Springer, 1st Edition, September 10, 2003, pp V
[3]. http://arri.uta.edu/acs/ee5322/HwkExams09/HWKhome.htm
[4]. A.Ukil, "Intelligent Systems and Signal Processing in Power Engineering", Springer, 1st Edition, 2007 pp 5-29.
[5]. http://www.mathworks.com/access/helpdesk/help/toolbox/nnet/index.html?/access/helpdesk/help/toolbox/nnet/&http://www.mathworks.com/products/neuralnet/description6.html.
[6]. C.Rehtanz, "Autonomous Systems and Intelligent Agents in Power System Control and Operation", Springer, 1st Edition, September 10, 2003, pp 37-42.
[7]. L. A. Zadeh, "Fuzzy sets and information granularity," in Advancesin Fuzzy Set Theory and Applications, 1979, pp. 3-18.
[8]. M. Ishizuka, K. **S.** Fu. and J. T. P. Yao, "Inference procedures and uncertainty for the problem-reduction method," Inform. Sci.vol. 28, 1982, pp. 179-206.
[9]. R. Yager, "Generalized probabilities of fuzzy events from fuzzy belief structures," Inform. Sci., vol. 28, 1982, pp. 45-62.
[10]. H. Ogawa and K. **S.** Fu, "An inexact inference for damage assessment of existing structures," International Journal of Man - Machine Studies, vol. 22, 1985, pp. 295-306.

[11]. Zi,Xing Chai, "Intelligent Control Principles, Techniques and Applications", World Scientific, Dec 18, 1998, pp 433.
[12]. Hung T.Nguyen, Nandipuram R.Prasad, Carol L.Walker, Wlbert A.Walker, "A First course in Fuzzy and Neural Control", CRC, 2003, pp 229-248.
[13]. Ján Vaščák, "Navigation of Mobile Robots Using Potential Fields and Computational Intelligence Means", Acta Polytechnica Hungarica, Vol. 4, No. 1, 2007, pp 63-74.