APPLICATION OF EVOLUTIONARY FUZZY SYSTEM IN AIRCRAFT CONTROL

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ABSTRACT

Usually fuzzy system takes into account of expert knowledge base. But to design fuzzy models and controllers we encounter a major difficulty in the identification of an optimized fuzzy rule base as well as membership function shapes and types. In fact, it is more difficult and time consuming for the expert to define a complete rule sets for a complex system that uses a large number of parameters. On the contrary, evolutionary fuzzy system widely used for optimization and learning process in which the membership function, shapes, types, fuzzy rule sets including the number of rules inside it are evolved using an evolutionary algorithm. A new approach to discovery of fuzzy rules using evolutionary algorithms and a flexible encoding method is proposed in this paper. The benefits of this methodology are illustrated for the control of aircraft system that shows better performance rather than existing fuzzy expert systems.

Keywords-- Artificial Intelligence (AI), Fuzzy Expert System, Evolutionary Algorithms (EAs), Membership Functions, Fuzzification & Defuzzification, Automatic Knowledge Discovery.

1. INTRODUCTION

Fuzzy logic is one of the AI (Artificial Intelligence) techniques first developed by Lotfi Zadeh in 1965[1]. It solves control problems in fuzziness and linguistic way. With its aid, complex requirements may be implemented in amazingly simple, easy maintained and inexpensive controllers. Fuzzy knowledge is expressed by the concept of fuzzy sets and linguistic variables. Previous automatic methods to extracts fuzzy are neural networks (NNs), fuzzy clustering, genetic algorithms (GAs) etc.

Evolutionary algorithms based method is represented to evolve an evolutionary fuzzy system a hybrid approach that consists of novel evolution strategy (NES). It not only can evolve the rule set, tune the membership functions and evolve the membership function types, but also scale well and is, therefore, useful for large complex problems.

2. FUZZY EXPERT SYSTEM

Its basic structure includes four main components: a *fuzzifier*, which translates crisp (real-valued) inputs into fuzzy values. An inference *engine* that applies a fuzzy reasoning mechanism to obtain a fuzzy output. A *defuzzifier*, which translates this latter output into a crisp value and a *knowledge base*, which contains both an ensemble of fuzzy rules [3].

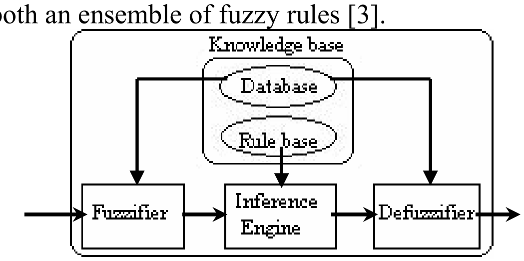

Fig. 1 Fuzzy expert system

2.1 Membership Function

Fuzzy set membership occurs by degree over the range (0,1) represented by a membership function. Various types of membership function[5]shown in fig.2.

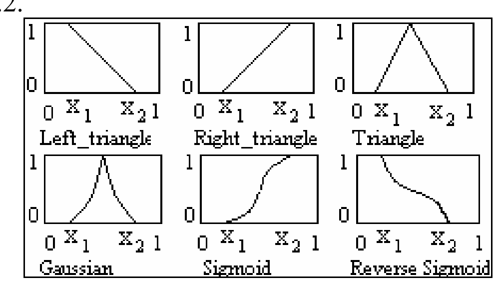

Fig. 2 Membership functions

Left triangle membership function:

$$f_{Left\_triangle} = \begin{cases} 1, & \text{if } x < x_1 \\ \dfrac{x_2 - x}{x_2 - x_1}, & \text{if } x_1 \le x \le x_2 \\ 0, & \text{if } x > x_2 \end{cases} \quad \ldots\ldots\ldots\ldots.. (1)$$

Right triangle membership function:

$$f_{Right\_triangle} = \begin{cases} 1, & \text{if } x < x_1 \\ \dfrac{x - x_1}{x_2 - x_1}, & \text{if } x_1 \le x \le x_2 \\ 0, & \text{if } x > x_2 \end{cases} \quad \ldots\ldots\ldots(2)$$

Triangle membership function:

$$f_{triangle}(x) = \begin{cases} 0, & \text{if } x < x_1 \\ 2\dfrac{x - x_1}{x_2 - x_1}, & \text{if } x_1 \le x \le x\dfrac{x_2 + x_1}{2} \\ 2\dfrac{x_2 - x}{x_2 - x_1}, & \text{if } \dfrac{x_2 + x_1}{2} < x \le x_2 \\ 1, & \text{if } x > x_2 \end{cases} \quad ..(3)$$

Gaussian membership function:

$$f_{Gaussian}(x) = e^{-0.5y^2} \text{ where } y = \frac{8(x - x_1)}{x_2 - x_1} - 4 \quad \ldots\ldots\ldots(4)$$

Four types of membership function are used (fig.3): Gaussian (00), Left_Triangle (10), Right_Triangle (01) and Triangle (11). A membership function is completely determined by three values: center (C), width (W), and the function type value (binary bit)[4].

Membership function type	Bits
Gaussian	00
Left_triangle	01
Right_triangle	10
Triangle	11

Fig. 3 Membership Function representation

3. EVOLUTIONARY ALGORITHM

Novel Evolution Strategy Algorithm (NES) [2] (proposed by Dr M.M.A. Hashem in1999) is used in this paper. Two important variation (genetic) operators of the NES algorithm are

1. Subpopulation Based Max-Mean Arithmetical Crossover (SBMAC)
2. Time Variant Mutation (TVM)

```
Algorithm_NES()
{
  t = 0;  /* Initilization the generation counter */
  Initialize_Population();
  Evaluate_Population();
  while(NOT termination condition satisfied) do
 {
  Apply_SBMAC();  /* Crossover operation */
  Apply_TVM();  /* Mutation operation */
  Evaluate_Population();
  Alternate_Generation();
  t++;  /* Increase the generation counter */
 }
}
```

4. EVOLUTIONARY FUZZY SYSTEM

Evolutionary fuzzy system combines the features of fuzzy system and evolutionary algorithm. Generally fuzzy system use expert knowledge base. But in complex system expert knowledge base is incomplete, cannot be easily described in linguistic form and also time consuming for expert to define a complete rule sets. Evolutionary fuzzy system extends traditional fuzzy system by a learning ability without changing the fuzzy rule framework and it generates fuzzy rules on the basis of the environment. Hence evolutionary fuzzy system shows better performance than the conventional fuzzy system.

4.1 Fuzzy Rule

Fuzzy rule extracted by evolutionary algorithm has the following form:

If D = T (Center(C), Width (W)),
S = T (Center(C), Width (W)) and
Φ = T (Center(C), Width (W))
Then V = T (Center(C), Width (W)) and
θ =T (Center(C), Width (W))

Where T(C,W) means the isoscales gaussian_shaped membership function whose center point is located on c and with width w and D,S and Φ are input variables of the fuzzy model and V, θ is the output variables.

4.2 Encoding

To completely represent a fuzzy system, each chromosome must encode all the needed information about the rule set and the membership functions. Fig.4 & Fig.5 shows the EA coding in details. Each individual consists of two parts. The first part involves the gaussians of all antecedents. The second part is dedicated to the enable bits.

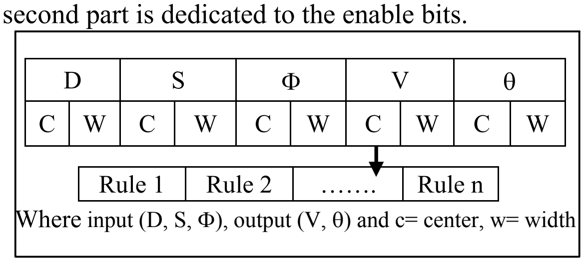

Fig. 4 Fuzzy model encoded in a chromosome

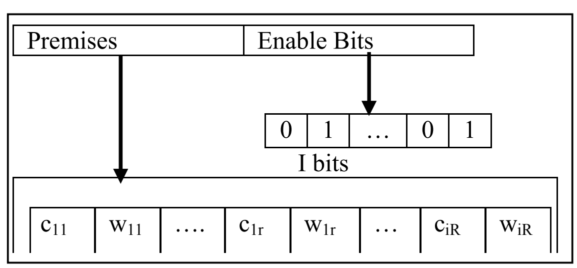

Fig. 5 EA encoding

Each chromosome in the population encodes the rules of the rule base of the fuzzy model as well as the membership functions of the variables.

5. PROBLEM DOMAIN

An interesting application of the linguistic variable is embodied in the fuzzy automatic aircraft control system as shown in fig. 6. Fuzzy system based control system lets aircraft move autonomously along a trajectory to touchdown on the runway.

5.1 Fuzzy Aircraft control system

The final approach and landing of an aircraft involve maneuvering and maintaining flight in an appropriate course to the airport and then along the optimum “glide path” trajectory to touchdown on the runway. The pilot executing such a landing must monitor cockpit instruments that display the position of the aircraft relative to the desired flight path and make appropriate corrections to the controls. These corrections are often accomplished by successive approximation and can be described linguistically as heuristic “rules of thumb” by expert pilots. Larkin designed and implemented a fuzzy autopilot controller, which demonstrated good results when tested on a flight simulator. This autopilot controls final approach and landing of the aircraft until just prior to touch down.

Three state inputs are monitored by the controller: rate of aircraft descent D, deviation from desired speed S , and deviation from glide-slope trajectory Φ (in degrees). Output or control actions are engine speed change V and elevator angle change θ (in degrees).

The arbitrary ranges of the variables are as follows:

$$0<D<300$$
$$0<S<100$$
$$-45<\Phi<45$$
$$0<V<50$$
$$-30<\theta<30$$

6. SIMULATION

The implementation of the evolutionary fuzzy system is written in c++ and compiled using the Borland c++5.02 compilers. This works develops fuzzy system for controlling the aircraft control system. Assume for this simulation the maximum acceptable number of fuzzy rule is 35, then the total length of the real part chromosome is 350.

After 1000 generation, we obtain the rules of the best chromosome that gives the minimum fitness

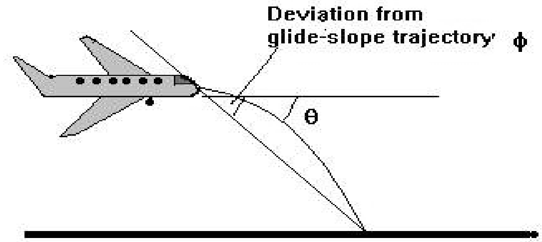

Fig.6 Diagram of Simulated fuzzy aircraft control system

error and also defuzzify to produce a numerical output value for the fuzzy set shown in fig.8.

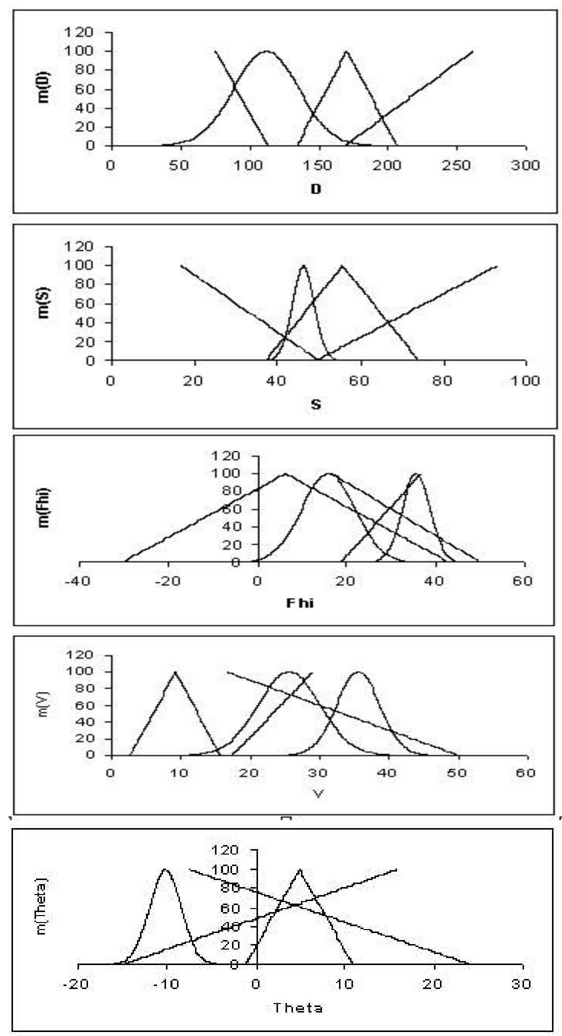

Fig.7 Membership functions curve for fuzzy-sets

6.1 Fuzzy Rule

Graphical representation of the membership functions of the 2 fuzzy rules are shown in fig.9 that If D and S and Φ then V and θ.

Type	D		S		Φ		V		Θ	
Bit	Center	Width	Center	Width	Center	Width	Center	Width	Center	Width
11	141.869	150.582	30.6874	2.44671	11.1816	84.078	5.65316	3.91011	-14.864	18.1011
01	77.2525	110.491	26.3403	4.01976	40.0919	32.3004	6.17479	2.58386	3.13212	22.922
10	129.009	131.6	11.3968	7.24008	28.2984	50.1772	6.73654	2.03485	-2.1946	47.2719
00	93.6443	122.793	27.8395	31.1477	25.5067	18.7842	8.56584	2.81876	-1.9867	16.0093

Fig.8 Numerical value of the fuzzy rule

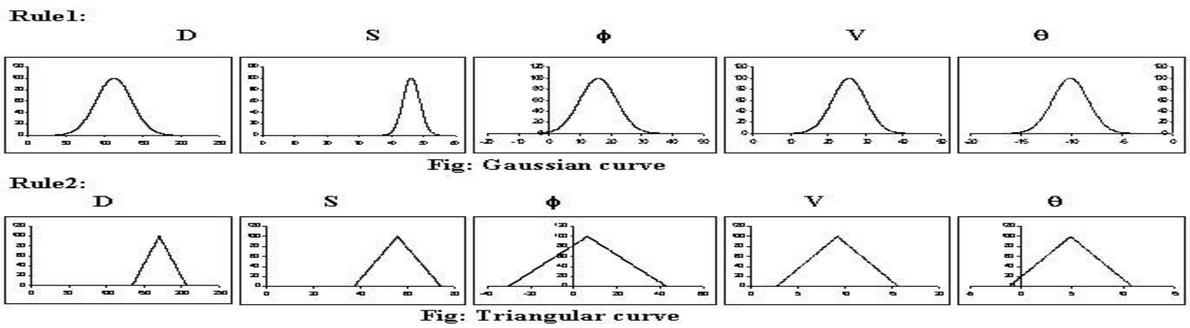

Fig.9 Sample of two fuzzy rules

6.2 Result

The fuzzy aircraft control system produced successful aircraft move autonomously along a trajectory to touchdown on the runway starting from any initial position by using fuzzy rules.

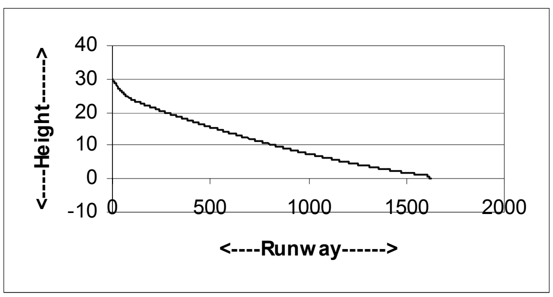

Fig.10 Sample aircraft trajectories for initial position(X,Y, Φ,D,S)=(25,30,30,150,30).

6.3 Evolution Histogram

The evolution histogram of generation versus fitness error (Tracking error) shows that as the number of generation increases the tracking error decreases fig.11

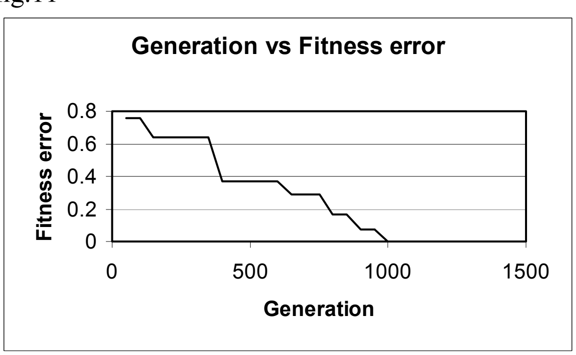

Fig.11 Generation vs Fitness error

7. CONCLUSION

This study presented an approach to develop and analyze a new fuzzy system by using evolutionary algorithms which can be applied successfully to the real world problems. Evolutionary fuzzy systems have been represented in which the membership function, shapes, types and the rule set, are evolved by using an Evolutionary (EA) algorithm.

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