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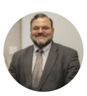

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Genetic Fuzzy Approach for Control and Task Planning Applications

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Genetic fuzzy is applied to two benchmark problems, the inverted double pendulum and the task assignment for cooperating UAVs classified as the polygon visiting multiple traveling salesman problem (PVMTSP). GA is used to define the membership functions and the rule base for the FIS that is used for solving the two benchmark problems. In this paper, we propose a genetic fuzzy controller to control an inverted double pendulum. We also show the effectiveness of the controller even when subjected to noise. For the PVMTSP, we propose a method of genetic fuzzy clustering that would be specific to MTSP problems and hence more efficient compared to k-means and c-means clustering. We also discuss how well our algorithm scales for increasing number of targets. The results are compared for two different polygon sizes.

Nomenclature

m_1,m_2	Mass of the pendulum bobs
L_1,L_2	Length of pendulum links
θ_1,θ_2	Angle of each link with the vertical
T_1,T_2	Torques applied by the controllers at each joint
MTSP	Multiple Traveling Salesman Problem
PVMTSP	Polygon Visiting MTSP
UAV	Unmanned Aerial Vehicle
GA	Genetic Algorithm
FIS	Fuzzy Inference System
D_q	Distance travelled by the q^{th} UAV

I. Introduction

Recent technological opportunities in both hardware and real-time implementation enable us to push the envelope with regards to introducing intelligence into aerospace systems design for numerous important applications such as propulsion systems,[1] satellite attitude control systems,[2] and collaborative control of a swarm of UAVs.[3,4] The mapping of sensor information, collected in real-time, is fused with the dynamic system model and operational and environmental databases onto a set of control actions and/or decisions which need to be computationally efficient, robust in face of uncertainties and noise, scalable and adaptable to dynamic variations to the mission while adhering to all the constraints of the specific application. The basic approach is to make most of what resources are available in order to get the best possible results. We are seeking a high performing, robust and scalable optimal action. Recent experience with the application of genetic fuzzy systems[1–4] has shown a great deal of potential.

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Intelligent control techniques are gaining traction and increased focus.[1] Fuzzy logic control is one such intelligent control technique and will be a cornerstone of this study. This nonlinear control design technique provides significant benefits in terms of design flexibility, universal approximator attribute and possible coupling with optimization processes. When coupled with the ability to capture expert or heuristic knowledge, and the ability to tune behavior in local envelopes of the operating space, fuzzy logic can be an indispensable control design tool in many applications. Fuzzy logic control also possesses inherent robustness due to having knowledge-based properties, making them good candidates for stochastic systems. One of the main challenges facing control designers is the tuning of the membership functions and the heuristics involved. Fuzzy logic controllers can have a variety of handles to impact performance, from the fuzzy input and output sets to the governing rule base. GA, a branch of evolutionary algorithms, will be utilized in this study to provide an autonomous guided search of the design space to develop a more optimized solution against the design requirements.

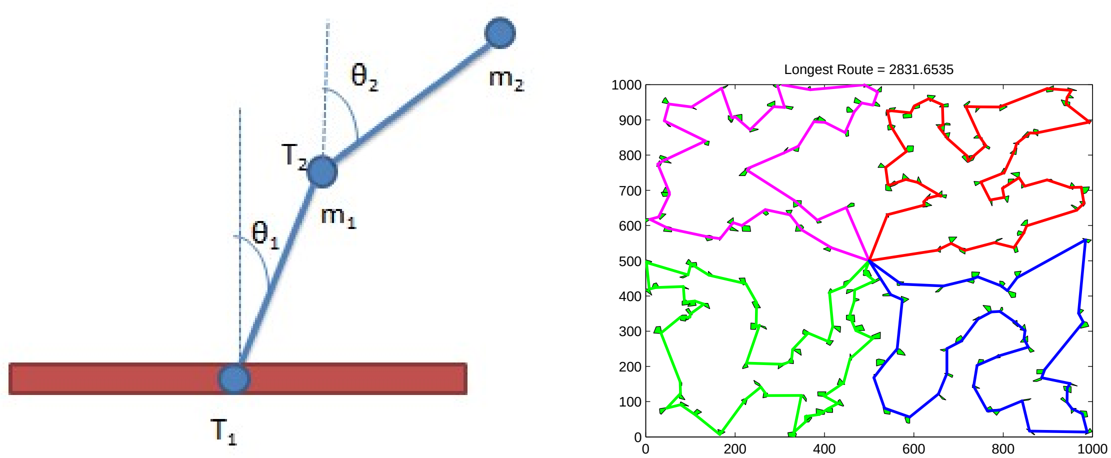
A. Problem Description

In this paper, we propose to apply genetic fuzzy logic to two benchmark problems: (1) Inverted double pendulum, (2) Polygon Visiting Multiple Travelling Salesman Problem (PVMTSP). The inverted double pendulum is an archetype for thrust vector controlled multi-staged rocket or missile or even multi-rotor UAV flight control. The PVMTSP, on the other hand, finds applications in UAV swarm routing where a number of UAVs start from a single depot, cover all the targets collaboratively and return back to the depot. Rather than targets being represented by points in the case of classical TSP, in the PVMTSP problem, each target is an area defined by a polygon. Here, the figures of merit include the computational time as well as the minimum time to complete the mission. The mission time is proportional to the minimum of the maximum distance amongst the UAVs. Hence, this is a min-max optimization problem. This paper also discusses how the algorithm scales with increasing number of targets.

1. *Double Pendulum*

The objective is to use a fuzzy controller to control an inverted double pendulum using two controllers at the two joints as shown in figure 1(a). T_1 and T_2 are the torques applied by the controller at the joints. GA is used to tune the fuzzy membership functions as well as the rule base to come up with the best possible solution, which settles at $\theta_1 = 0$, $\theta_2 = 0$, in minimum time. The equations of motion are given below:

$$(m_1 + m_2)L_1^2\ddot{\theta}_1 + m_2 L_1 L_2 \ddot{\theta}_2 cos(\theta_1 - \theta_2) + m_2 L_1 L_2 \dot{\theta}_2^{\,2} sin(\theta_1 - \theta_2) + (m_1 + m_2) g L_1 sin\theta_1 + T_1 = 0 \quad (1)$$



(a) Double Pendulum

(b) PVMTSP

Figure 1. The two benchmark problems

$$m_2L_2^2\ddot{\theta}_2 + m_2L_1L_2\ddot{\theta}_1 cos(\theta_1 - \theta_2) - m_2L_1L_2\dot{\theta}_1^{\,2} sin(\theta_1 - \theta_2) + m_2gL_2 sin\theta_2 + T_2 = 0 \tag{2}$$

2. PVMTSP

This is basically an MTSP with targets represented by polygons of finite area. Four UAVs start from a common depot, cover 200 targets that are spread over a 1000 units x 1000 units space, and return to the depot in the shortest time. The polygon radius is assumed to be 10 units. A genetic fuzzy approach is used to cluster the targets among the four UAVs such that almost equal distance is covered by each UAV. Figure 1(b) shows a PVMTSP solution.The objective function can be written as[5]

$$minimize\ D_{max} = max_q(D_q) \tag{3}$$

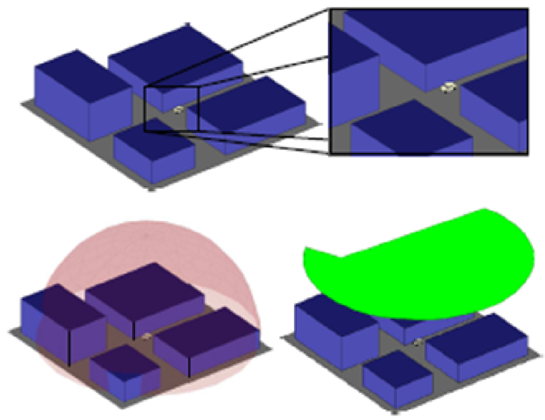


Figure 2. Creation of visibility polygons[6]

As shown in figure 2, the polygons in this class of problem can designate a visibility area of a UAV. These are created by taking some sphere around the target with the radius of the desired sensor or weapon onboard the UAV, removing sections of the sphere blocked by obstacles or terrain, and slicing a plane at some constant altitude.

II. Methodology

A. Double Pendulum

Fuzzy logic is used to determine the torques acting on the two joints, T_1 and T_2. In order to reduce the computational complexity, each of the inputs and outputs are defined by just three membership functions as shown in figure 3. GA is used to tune a nine element vector R. The first 5 elements,R(1:5), represent the rules as shown in table 1 and R(6:9) represents the boundaries of the membership functions as shown in figure 3. The membership functions are assumed to be symmetric around zero. The rule-base is same for both the controllers T_1 and T_2. AND operator connects the inputs θ and $\dot{\theta}$. For example,

$$If\ \theta_1\ is\ N\ AND\ \dot{\theta}_1\ is\ P,\ then\ T_1\ is\ R(1) \quad .$$

Table 1. Rule base for double pendulum

θ, $\dot{\theta}$	N	ZO	P
N	P	P	R(1)
ZO	R(2)	R(3)	R(4)
P	R(5)	N	N

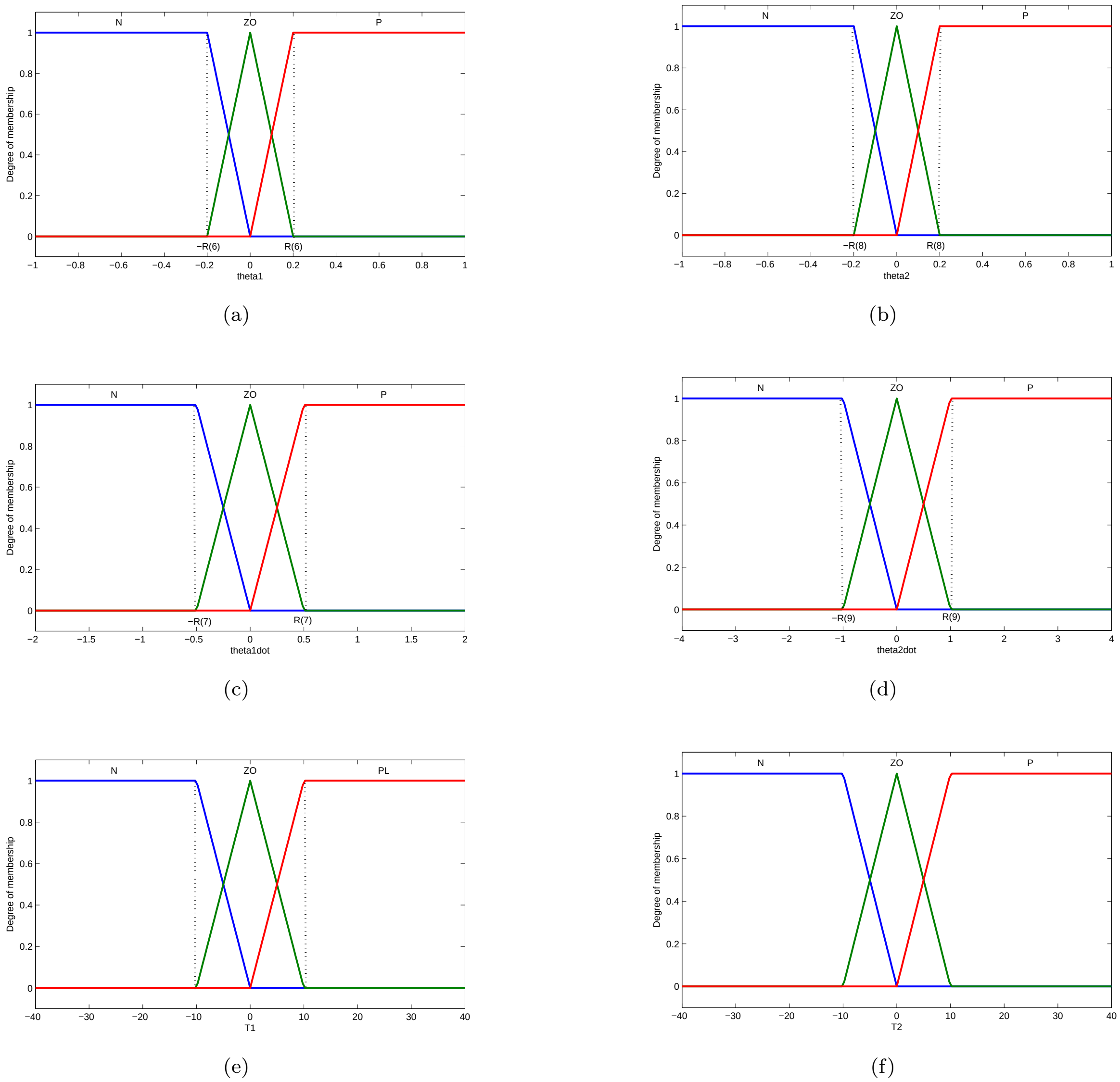


Figure 3. Membership functions

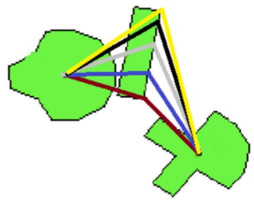
B. PVMTSP

Fuzzy Clustering Method

The fuzzy clustering method is a subset of the methods from previous work[3] that similarly utilizes a cluster-first approach to solve the PVMTSP. Here the angle between the depot and the targets is considered for clustering rather than the Cartesian coordinates. The radius measurement is ignored for this problem. A clustering FLS develops an initial guess at the proper clustering of the targets.

The convex hulls of this initial is calculated and then the solution is refined through additional FISs which analyze a single target at a time. Each convex hull is analyzed, and its relative number of targets and target densities are calculated. FISs then swap points between each of the clusters in an effort to achieve dense clusters of equal and minimal size. This process ends once the clusters are within some threshold of each other in these two statistics.

To determine which point on the polygons the UAV will visit, a simple algorithm is utilized which iterates around a number of points on each side of the polygon. The combined length of the two lines connecting the point on the polygon in question with the selected points on the polygon before and after it, as shown in figure 4. This iterates over the route three times, at which point the solution converges. Lin-Kernighan then solves the individual TSPs of these points for each UAV.



$$Distance = \sqrt{\left((y_{i,n} - y_{i-1})^2 + (x_{i,n} - x_{i-1})^2\right)} + \sqrt{\left((y_{i+1} - y_{i,n})^2 + (x_{i+1} - x_{i,n})^2\right)}$$

Figure 4. Point selection on each polygon

Genetic Fuzzy Clustering Method

In one of our previous works,[5] we used a cluster first approach using K-means and then applied 2-opt to solve the individual clusters, which achieved high levels of performance. But the K-means and even fuzzy C-means are purely distance optimizing clustering algorithms and do not optimize appropriately for MTSP problems. In the genetic fuzzy clustering method, an FLS[7] divides the targets into four clusters and each cluster is solved using a TSP solver like Lin-Kernighan method. The technique shown in figure 4 is used to find the optimal point of contact on each polygon. GA is also used to tune the rulebase and the membership functions of the FLS. But unlike the case of the double pendulum, the GA tunes the rulebase and membership functions separately. The flowchart for this genetic fuzzy approach is shown in figure 5.

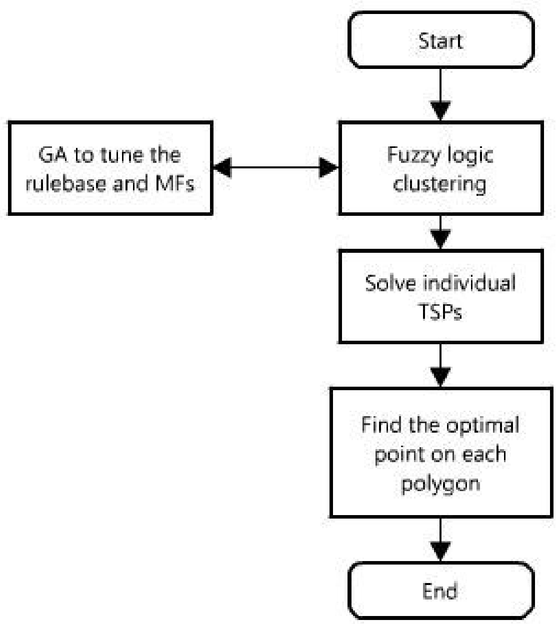


Figure 5. Flowchart of Genetic Fuzzy Clustering Method for PVMTSP

III. Results

All the results were obtained with a laptop utilizing MATLAB with an Intel i3 2.3GHz processor and 4GB of RAM.

A. Double Pendulum

The rulebase obtained after tuning is shown in table 2 and it matches our intuition. The membership function boundaries are obtained as R(6) = 0.1087, R(7) = 0.5912, R(8) = 0.6706 and R(9) = 1.0361. The system response is shown in figure 6. The system was tested for different starting positions and in each case, the reponse settles within 5 seconds.The genetic fuzzy controller works well even when it is subjected to noise in the angle measurements. The response is shown in figure 7.

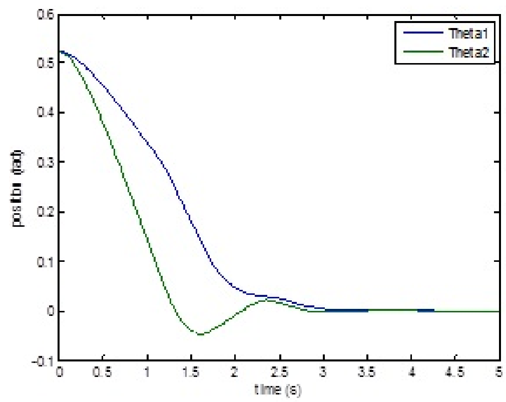
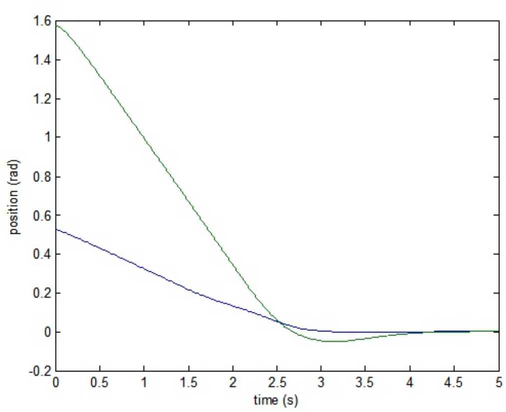


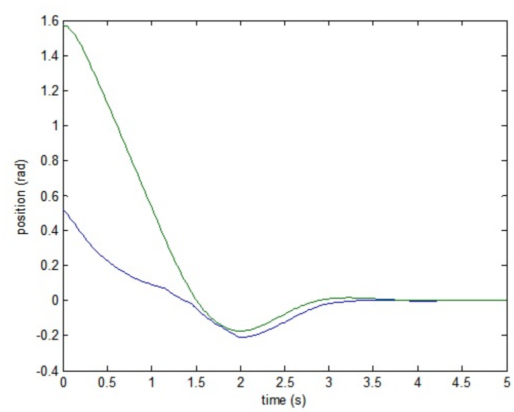
Figure 6. Time histories of θ_1 and θ_2

Table 2. Rule base for double pendulum after tuning

θ, $\dot{\theta}$	N	ZO	P
N	P	P	P
ZO	ZO	ZO	N
P	ZO	N	N



(a) 5% noise

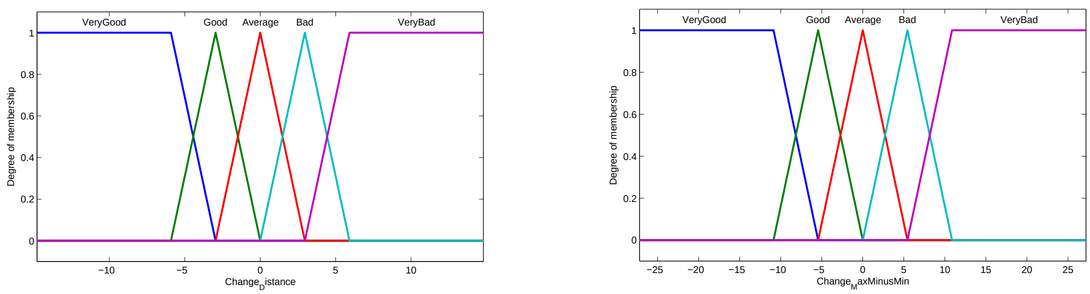


(b) 10% noise

Figure 7. Time histories of θ_1 and θ_2 when noise is applied

B. PVMTSP

The FIS used for clustering[7] has two inputs, ChangeMaxMinusMin and ChangeDistance, which are respectively the change in maximum minus minimum distance and the change in maximum distance as a result of shifting points, measured as a percentage. The input membership functions are tuned using GA and the results are shown in figure 8. The membership functions are assumed to be triangular and of equal widths.



(a) ChangeDistance

(b) ChangeMaxMinusMin

Figure 8. Tuned membership functions for PVMTSP

The results obtained are compared with fuzzy clustering method[3] and is shown in table 3. The values shown in the table are the averages obtained over 100 runs of the code for two different polygon radii. Small and large polygons refer to polygons of radius 10 units and 30 units, respectively. A larger polygon represents a larger area of visibility. It can be observed that our approach gives a 6% better result compared to that obtained using fuzzy clustering method at the expense of computational time. It was found during the course of our work that the 2-opt algorithm does not perform well when the targets are close together. Hence, Lin-Kernighan method, which is an extension the 2-opt algorithm, is used to solve individual TSPs.

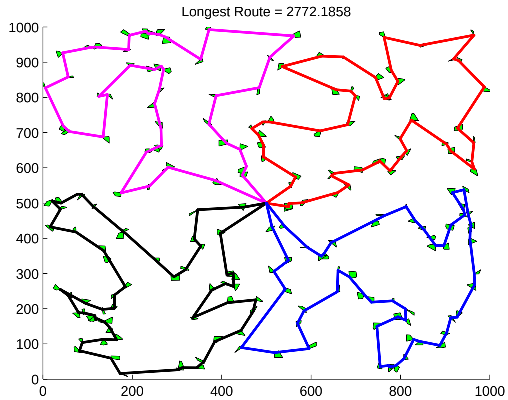
Table 3. Comparison of results obtained for PVMTSP

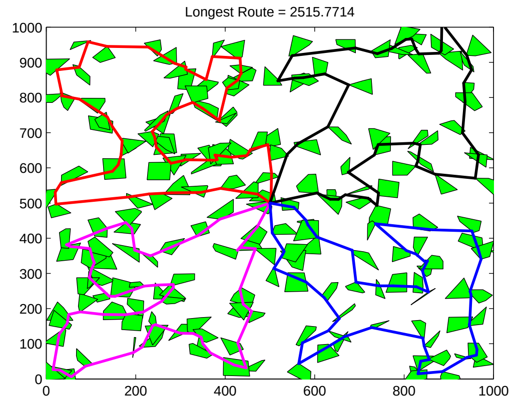
	Small polygons		Large polygons	
	Largest distance	Computational time (in seconds)	Largest distance	Computational time (in seconds)
Fuzzy clustering method	2919	6.0	2498	8.2
Genetic fuzzy clustering method	2754	80.8	2376	96.3
Normalised values with respect to fuzzy clustering method	0.9434	13.5	0.9511	11.7

The computation time for the fuzzy clustering method is quite low due to the fact that only simple algorithms, FLSs, and the Lin-Kernighan solver are utilized, allowing the algorithm to scale well. Quality results are obtained, however there are weaknesses present in the clustering method. The strength of the initial guess has a significant effect on the quality of the final result. Additionally, the refinement process occasionally performs suboptimal swaps of clusters and nearest-neighbor points. Increasing the points utilized for this check could help reduce suboptimal swaps, though computation time would increase to some degree.

The solutions to the PVMTSP, using genetic fuzzy clustering method, for small and large polygons are shown in figure 9. The presence of a lot of straight lines passing through the polygons in the solution shown in figure 9(b) is indicative of the effectiveness of the algorithm in finding the optimal connection points on each polygon.

Figure 10 shows the variations in computational time and the longest distance as the number of targets are changed. The computational time increases steadily as the number of targets are increased. From figure 10(b), it can be seen that the genetic fuzzy approach gives better distances as compared to the fuzzy clustering method.

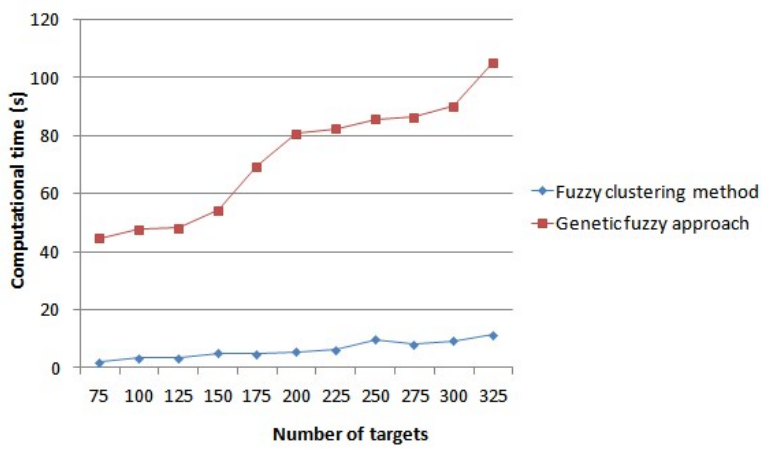




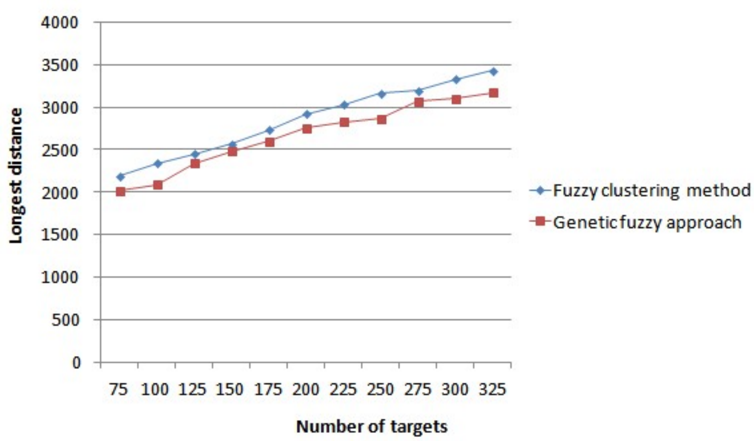
(a) Polygon radius = 10 units

(b) Polygon radius = 30 units

Figure 9. PVMTSP solution with (a) small and (b) large polygons



(a)



(b)

Figure 10. Computational time and longest distance in relation to number of targets

IV. Conclusions & Future Work

This research has shown the applicability of genetic fuzzy systems to dynamic systems and path planning. While fuzzy logic by itself works well for these problems, tuning the parameters involved to satisfy a specific requirement might need a lot of trial and error to be done by the researchers. Incorporating GA to tune these parameters solves this problem.

The results shown for double pendulum indicate that the genetic fuzzy controller works well even in the case of noisy measurements. This is a very important result in that all real-life applications are subject to measurement noise. A classical controller, such as a PID controller, will have a much higher settling time under noise whereas our genetic fuzzy controller is unaffected.

In the case of the PVMTSP, the genetic fuzzy approach shows an improvement in optimal distance as compared to the fuzzy clustering method.[3] The higher computational time is due to the clustering algorithm[7] which solves the TSP in each iteration to come up with an optimal solution. The computational time could be decreased by using certain parameters characterising the topology of the problem instead of solving the TSP in each iteration. An investigation into using only the angle values for the clustering may provide additional reductions in computational time for the genetic fuzzy approach for this single-depot case. But, how this affects the optimal distance remains to be seen.

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