The Application of Fuzzy Neural Networks in Formation Control for Multi-robot System

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Abstract

The formation problem of multi-robot is a type problem in cooperation and it is one of challenging research directions of multi-robot system. Aiming at the formation control problem, in this paper we propose a kind of hybrid architecture firstly, which combines the reactive architecture based on Motor Schema with the hierarchical architecture. Secondly we design four kinds of basic behaviors based on the reactive architecture, and design each of behaviors using fuzzy neural networks. Lastly we use nerve cell fuse the outputs of each of behaviors qua the final outputs of system, which controls executive appliance to act. This method put forward enhances intelligence and the environmental applicability in this paper. The simulation results validate the feasibility of this method.

1. Introduction

Formation is a typical of problem in multi-robot system. After formation the multi-robot system has an extensive application in military affairs, aviation spaceflight and industrial field. For example, it may spy, search and safe patrol in military affairs \cite{1}. And it also may rescue after earthquake or flood in some special occasions.

What is called formation control is a control technique, which requests multiple robot keep a certain of formation and at the same time adapts environmental restriction during the course of arriving destination. Many overseas and domestic scholars carry through a large of and significative study. Literature \cite{1,2,3} summarizes the formation control methods, which are behavior-based method, artificial potential method, leader-follower method, virtual structure method, circulation method, model forecast method and distributing control method etc. And merit and shortcoming of each of methods is analyzed.

Thereinto the behavior-based method is composed of a series of behavior. Each behavior has its objection and task. The inputs of each behavior are information of sensors or outputs of other behaviors. The outputs of each behavior are used to control executive appliance or serve as the inputs of other behavior. The key problems of behavior-based are the design of each of behavior and the coordinated mechanism of behavior.

In this paper, ultrasonic array sensor and collision sensor and milemeter is adopted. In many sensors system, the environmental information of each sensor has the uncertainty property. Hereby the behaviors are designed after fusing to carry through formation control, which is an uncertainty inference course. Because of the each unique characteristic of fuzzy logic (FL) technology and neural networks (NN) technology, the fuzzy neural networks (FNN) control system which is formed through combing fuzzy logic with neural networks, may distill fuzzy rules and create fuzzy member function automatically\cite{4,5}. For the sake of improving environmental adaptability of formation control and the precision of formation keeping, this paper adopts FNN to design each behavior and adopts nerve cell to carry on behavior selection. The simulation results validate the feasibility of this method.

2. The architecture of formation control

The architecture is an important content of multi-robot system, it study mostly how to organize and control hardware and software system of robot to realize function which robot need achieve. During the development course of robotics, many scholars put forward a large of kind characteristic architecture, for example, the traditional architecture, the subumption architecture, the reactive architecture, the hierarchical architecture and hybrid
architecture. According to the request of multiple robot formation, we propose a hybrid architecture which combines the reactive architecture based on Motor Schema \[6\] by R.C.Aarkin with the hierarchical architecture. Figure 1 is the hybrid architecture of formation control for multiple robots. We can see that from Figure 1 the whole system adopts the hierarchical architecture, and the formation control module adopts the reactive architecture. Aiming at different request of task and demand of environment, this hybrid architecture adopts module device, reconstruct easily and is fit for dynamic and open environment.

From Figure 1, we know that entire system includes communications module, sensor module, formation control module, executive appliance module and environment module. In this paper supposing each robot which is self-determination mobile robot, can identify environment and confirms position and posture on the basis of sensors oneself. The design of formation control module by FNN is an emphasis. Next, we will introduce the communication module and sensor module simply.

### 2.1. Communication module

In multi-robot system, communication module adopts blackboard communication \[7,8\]. During the course of movement each of step, robot sends self information to blackboard, at the same time gains the information of other robot and system. Blackboard communication can make communication concentratedly, reinforces real-time and dynamic property of system and implements easily. As long as it has the homology delay of communication, behavior can be controlled precisely.

### 2.2. Sensor module

In this paper we adopt ultrasonic array sensors, collision sensor and milemeter. Collision sensor examines mostly whether robots collide each other or robots collide with static obstacle. Milemeter confirms position of robot oneself. Ultrasonic array sensors examine the obstacle position of environment. Ultrasonic array sensors are fixed the former and two sides of robot. Figure 2 is the sketch map of ultrasonic array sensors.

The outputs of ultrasonic array sensors are a series of distance value. Through the directional angle decided in advance is that ultrasonic array sensors relative to robot, the robot can know whether it have obstacle and the distance of relation to obstacle. We can carry through the design of formation control on the basis of the outputs of ultrasonic array sensors and the information of other robots.

### 3. Fuzzy neural networks

In this paper, because we will use FNN to design each behavior of formation control, we introduce the structure of FNN. At present, FNN is applied abroad in control fields, because FL and NN have the reparative character each other. They belong to no module estimator. They are tools which can handle uncertain property and nonlinear property. In fuzzy system knowledge is distilled and expressed conveniently. But FL is short of self-adaptability and self-learning. NN has the property of the parallel compute, the distributed information storage, fault tolerance ability and self-learning et al. But NN is unfit for express knowledge rule-based. So FNN have the merit of FL and NN. FNN have two kinds of structure form: FNN based on standard model and FNN based on Takagi-Sugeno model. In this paper we adopt the former. Figure 3 is its structure.

The first layer is input layer. Each node of the layer connects directly with every ponderance of input vector, its function sends inputs to next layer. The number of node: \( N_1 = n \).
The second layer is fuzzifier layer. Each node represents a kind of language variable value, such as NB, PS etc. Its function computes member function (MF) \( \mu_j \).

Thereinto \( \mu_j^i \equiv \mu_j^i(x_i), i = 1, 2, \cdots, n, j = 1, 2, \cdots m_j \),
n is the dimension of input, \( m_j \) is fuzzy partition of \( x_i \). The number of node: \( N_2 = \sum m_j \).

The third layer is fuzzy rule layer. Each node represents an item fuzzy rule. Its function is used in computing the fitness of each rule, as well as

\[
a_j = \min \{ \mu_1^i, \mu_2^i, \cdots, \mu_n^i \}, \quad m = \prod m_j .
\]

The number of node: \( N_3 = m \).

The fourth layer is normalization layer. The number of node: \( N_4 = N_3 + m, N_3 = \text{max} a_j = \sum a_j \).

The fifth layer is defuzzifier layer. The centroid method:

\[
y_i = \sum w_j a_j, \quad i = 1, 2, \cdots, r .
\]

The learning method of FNN adopts BP arithmetic, which is used abroad. Reference [9] gives out the correlative learning arithmetic. So we do not give unnecessary details.

Here supposing that robots confirm own position according to their own inner sensors. We choose two input variable and two output variable for move-to-goal behaviour. The input variable are \( \phi \) and \( z \). \( \phi \) is the angle between the movement direction and the object direction of robots. \( z \) is the distance between the current position and the object position of robot. The output variable is \( \Delta v_{\text{avg}} \) and \( \Delta \theta_{\text{avg}} \). \( \Delta v_{\text{avg}} \) is the next step velocity of robot. \( \Delta \theta_{\text{avg}} \) is the angle which the robot circumrotates during the next step.

The above parameter is blurringed as follows:

\( \phi \): NL (negative big), NM (negative medium), NS (negative small), Z (zero), PS (positive small), PM (positive medial) and PL (positive big).

\( z \): VN (very near), NR (near), FR (far), VF (very far)

\( \Delta v_{\text{avg}} \): Z (zero), VS (very slow), S (slow), F (fast), VF (very fast).

\( \Delta \theta_{\text{avg}} \): NL (negative big), NM (negative medium), NS (negative small), Z (zero), PS (positive small), PM (positive medial) and PL (positive big).

The fuzzy sets of the language variable domain, such as NL, NM etc. is described by MF \( \mu(x) \). \( \mu(x) \) is confirmed by adopting statistic method and using operation experience of manipulator. Here the each MF is triangle function. The MF of variables \( \phi, z, \Delta \theta_{\text{avg}} \) and \( \Delta v_{\text{avg}} \) are shown in Figure 4. It is the initial value of MF. The center of MF may be changed by training neural networks (NN).

\[\text{Figure 3} \quad \text{The fuzzy neural networks frame based on standard model}\]

4. The realization of formation control module

In this paper, we adopt behavior-based method to carry on formation control. The structure is the big dashed part of Figure 1. The behavior-based method makes the robots bring the needed entire behavior through designing the basic behavior of robots and the local control rules. The local controller is composed of a series of behavior. Each robot has basic behavior which has object and task themselves. In formation control the behaviors of robot are divided into move-to-goal behavior, keep-formation behavior, avoid-static-obstacle behavior and avoid-robot behavior. Adopting FNN to design each behavior, this is the core part of this paper.

4.1. The design of move-to-goal behavior

4.2. The design of avoid-static-obstacle behavior

The movement course from the start position to the target position, the sensors of robot detect the obstacle information in sample time. According as this, the robots make the next step decision. We choose three input variable which are \( d_i (i = 1, 2, 3) \) and two output variable which are \( v_{\text{avg}} \) and \( \Delta \theta_{\text{avg}} \). \( d_i (i = 1, 2, 3) \) denotes the obstacle distance of the left, the former and the right relative to
robot. $v_{aso}$ is the next step velocity of robot. $\Delta \theta_{aso}$ is the angle which the robot circumrotates during the next step.

hereinto, $d_1 = \min(s_1, s_2, s_3) \ , \ d_2 = \min(s_4, s_5, s_6, s_7) \ , \ d_3 = \min(s_8, s_9, s_{10})$ . 
\[d_i = \{1, 2, 3\}\] is fuzzifier as: VN(very near), NR(near), FR (far)

The fuzzification course $v_{aso}$ and $\Delta \theta_{aso}$ are same as the $v_{neg}$ and $\Delta \theta_{neg}$ . 

MF is triangle function. The center of MF may be changed by training NN.

4.3. The design of avoid-robot behavior

Avoid-robot behavior is designed through the sensors and the communications module. In Figure 5, as an example to robot2, the arrow is the movement direction of robot. The inputs of this behavior include:

1. The angle $\varphi$: $\varphi$ is the nip angle between $OA$ and $CA$.

2. The time difference value $\Delta t = \frac{t_{robot2} - t_{robot1}}{v_{robot1}}$ and $t_{robot2}$ are the time which robot1 and robot2 arriving at the A point respectively. A point is collision point. 

3. Distance $d$: which is the distance between robot and the other robot. $d = OA$ . 

Thereinto, $\varphi$ includes the velocity direction information of other robot, and $\Delta t$ includes the velocity size information of other robot.

The outputs variable of the behavior is $v_{ar}$ and $\Delta \theta_{ar}$, $v_{ar}$ is the next step velocity of robot. $\Delta \theta_{ar}$ is the angle which the robot circumrotates during the next step.

**Figure 5** The collision sketch map of robots

The above parameter is fuzzifier as follows:

$\varphi$: VS (very small), S (small), M (medium), L(big), 
VL (very big)

$\Delta t$: NL (negative big), NM (negative medium), NS (negative small), Z (zero), PS (positive small), PM (positive medial) and PL (positive big)

D: VN (very near), NR (near), FR (far)

The fuzzification course of $v_{ar}$ and $\Delta \theta_{ar}$ are same ans the $v_{neg}$ and $\Delta \theta_{neg}$ . 

MF is triangle function. The center of MF may be changed by training NN.

4.4. The design of keep-formation behavior

Keep-formation behavior is designed through the sensors and the communications module. In this paper we adopt the control strategy based leader-follower method to keep formation. According to the information of leader sending it's the next step, each follower computes its own perfect formation position $\left[ x_{fb}, y_{fb} \right]$, which is the object of the follower next step. $\Delta t = \sqrt{(x_{fb} - x_c)^2 + (y_{fb} - y_c)^2}$, which is the distance between the current position $[x_c, y_c]$ and $\left[ x_{fb}, y_{fb} \right]$.

So we choose $\Delta t$ by way of input variable of keep-formation behavior. $i$ is the number of follower robot.

$\Delta t$ is fuzzifier: Z (zero), VS (very small), S (small), B (big)

The outputs of keep-formation behavior are $v_{kf}$ and $\Delta \theta_{kf}$. The fuzzification course $v_{kf}$ and $\Delta \theta_{kf}$ are same as the $v_{neg}$ and $\Delta \theta_{neg}$ .

MF is triangle function. The center of MF may be changed by training NN.

According to the design of above four behaviors, we use four FNN to realize them.

From the above analysis, we may use four FNN to realize four behaviors. The FNN of move-to-goal behavior has two inputs and two outputs, the nerve cell number of each layer is 2, 11=7+4, 28=7+4, 28 and 2. The FNN of avoid-static-obstacle behavior has three inputs and two outputs, the nerve cell number of each layer is 3. 9=3+3+3, 33 and 2. The FNN of avoid-robot behavior has three inputs and two outputs, the nerve cell number of each layer is 3, 15=5+7+3, 105=5 × 7 × 3, 105and 2. The FNN of has i inputs and two outputs, the nerve cell number of each layer is 1, i, 4i, 4i', 4i' and 2. The number of fuzzy rule layer is the maximal number which is confirmed by above FNN.

The initial MF of all variable is triangle function. The training sets of FNN are produced by the formation control which adopts fuzzy logic control. After the training, fuzzy rule and MF are automatic produced. Then fixupping the value of FNN, the testing sets may test FNN.

4.5. The design of behavior selection by nerve cell

The first issue of behavior-based formation control method is designing each behavior, which is introduced above. The second issue is the behavior selection, as well as the behavior synthesis or behavior decision, i.e. the small dashed part of Figure 1. At present, there are three kinds of the behavior selection mechanism: the weighted average method, suppression of behavior method and fuzzy logic method [1]. Reference [10] adopts
normalization method of a kind of adjustable weight value, as: \( V_{\text{direction}} = \text{normalize}(w_1v_{mg} + w_2v_{ar} + w_3v_{af} + w_4v_{aso}) \)

Thereinto \([w_1 w_2 w_3 w_4]\) is the adjustable weight value, and is devised the subsection function. In this paper we put forward a kind of new method which carry on behavior fusion using nerve cell. Nerve cell is the simplest nerve cell, which its threshold is zero.

According to each behavior and its outputs designed by the fourth chapter, we design the two behavior fusion centers which are velocity nerve cell and angle nerve cell. The velocity nerve cell has four input variables and one output variable. The four input variables are \(v_{mg}, v_{ar}, v_{af}, \text{ and } v_{aso}\), and the output variable is \(v_{final}\). The angle nerve cell has four input variables and one output variable. The four input variables are \(\Delta \theta_{mg}, \Delta \theta_{ar}, \Delta \theta_{af} \text{ and } \Delta \theta_{af}\), and the output variable is \(\Delta \theta_{final}\). The nerve cell of fusion velocity is shown as Figure 6.

![Figure 6](image)

\[\text{Figure 6 The nerve cell of fusion velocity}\]

Similarly, we can design the nerve cell of fusion angle. The training sample sets are produce by adopting the method of reference [10]. After training, the nerve cell of fixing up the weight value may carry on behavior selection.

### 5. Simulation study

The simulation environment is nonstructural plane environment. The simulation is three robots named \(R_1, R_2, R_3\) keeping triangle geometry shape from the start position \(S1(5,15), S2(3,17), S3(3,13)\) to the target position \(G1(25,15), G2(23,17), G3(23,13)\) avoiding collision. The robots in simulation have three postulates: the step of robot is 0.5 m. The step of leader is 0.5 × robot and its radius is 0.2 m in simulation. The maximum detection range of sensors is 1.5 m.

The simulation result is shown as Figure 7. According to Figure 7, we infer that the multiple robots can realize formation control in the simulation environment including multiple or simple static obstacle by using this novel method proposed in this paper.

## 6. Conclusions

In this paper the reactive architecture is combined with the hierarchical architecture and a kind of hybrid architecture is designed. In this architecture, we use FNN to design each behavior, and carry on behaviour selection by nerve cells. From the simulation result we can see that the proposed method may realize formation control in complex and nonstructural environment. Owing to using fuzzy control, self application is improved in multi-robot system relative to environment. The neural networks may realize automatic distill fuzzy rules and MF, and enhance the intelligence of multi-robot system.

![Figure 7](image)

(a)Multiple static obstacles  
(b)Single static obstacle

**Figure 7 The simulation results of multi-robot formation**

### References


