Research on Robot Motion Control Based on Variable Structure Fuzzy Neural Network Based on T-S Model

Jingyu Li
College of Information and Electrical Engineering, Shandong Jianzhu University, Jinan, Shandong250101, China
lijingyu@sdjzu.edu.cn

Abstract. The motion robot system is a nonlinear, strong coupling, non-integrity constraint control system, and its motion control has always been a hot topic in the control field. Aiming at the problem that the fuzzy neural network controller has too large computational complexity and poor anti-interference ability to the outside world, the paper proposes a fuzzy neural network control algorithm for TS, which reduces the computational complexity of the neural network and makes the closed-loop system of the robot more stable. The simulation experiment proves that the fuzzy neural network algorithm based on T-S makes the controller more resistant to external disturbances, and can maintain a high level of control even in harsh environments.

1. Introduction
Intelligent mobile robots are generally in an unstructured environment. The surrounding environment information is often uncertain and may change with time. Therefore, robots must be able to perceive the surrounding environment effectively and reliably, and can analyze, fuse, and autonomously decide. Any kind of intelligent mobile robot must rely on a sensor or a combination of sensors to get some estimation of its own environment, and with appropriate sensor information processing methods, make decisions based on control strategies, complete obstacle avoidance and the task of path planning implements autonomous navigation.

Fuzzy neural networks have been successfully applied to the motion control of robots [1]. However, when the external disturbance is relatively large and the environmental change is relatively fast, the effect of fuzzy neural network control is not ideal due to the lag of neural network learning, and even the control stability is not as good as the fuzzy controller. To this end, this paper proposes a robot T-S fuzzy neural network control method based on hybrid learning algorithm. The whole controller adopts the immune genetic optimization parameter of the membership function (center position and width of the membership function) in the offline state, and uses the neural network self-learning to adjust the parameters of the membership function in the online state, thereby reducing the computational complexity of the neural network and enhancing the robot. The fuzzy algorithm is automatically adjusted by the post-network to improve the robustness and adaptability of the entire controller, ensuring that the control performance remains at a high level even under severe conditions [2].
2. T-S fuzzy neural network model
In the fuzzy system, there are two main methods for expressing the fuzzy model: one is that the posterior of the fuzzy rule is a fuzzy set of output, such as NB, PB, etc.; the other is that the fuzzy rule is the input linguistic variable. Since the model representation was first proposed by Takagi and Sugeno, it is often referred to as the T-S model of the fuzzy system. The T-S model is an essentially nonlinear model that is easy to express the dynamic characteristics of complex systems. Since the output components of the conclusion part are composed of linear equations, it is easy to identify the conclusion parameters. Figure 1 shows the T-S fuzzy neural network model.

![Figure 1. T-S fuzzy neural network model.](image)

The implied conditional statement of the T-S fuzzy model is "if \( x \) is \( A \), then \( y = f(x) \)." Where "if \( x \) is \( A \), then \( y = f(x) \)" is a linear function of \( x \), the essence of which is that the "if" part of the fuzzy rule is ambiguous and the "if" part is deterministic. Set to \( R_i \) the \( i \)-th fuzzy rule, the continuous T-S fuzzy system model can be described as:

\[
\begin{align*}
R^i: & \text{if } x_1 \text{ is } F^i_1 \text{ and } \ldots \text{ and } x_n \text{ is } F^i_n, \\
& \text{then } x(t) = A_i x(t) + B_i u(t), \\
& y(t) = C_i x(t) + D_i u(t), i = 1, 2, \ldots, r
\end{align*}
\]

Where \( F^i_j \) is a fuzzy set, \( i \) is a fuzzy rule number, \( x(t) \in R^n \) is a state vector, and \( u(t) \in R^n \) is a constant matrix in which the input vector \( A_i, B_i, C_i, D_i \) is an appropriate dimension. The discrete T-S fuzzy system model can be described as:

\[
\begin{align*}
R^i: & \text{if } x_1 \text{ is } F^i_1 \text{ and } \ldots \text{ and } x_n \text{ is } F^i_n, \\
& \text{then } x(k+1) = A_i x(k) + B_i u(k), \\
& y(k) = C_i x(k) + D_i u(k), i = 1, 2, \ldots, r
\end{align*}
\]
Among them, \( x_k, F_k^i, i = 1, \ldots, f, k = 1, \ldots, n \) is the input state variable and fuzzy set of the fuzzy system respectively. \( x = [x_1(k), x_2(k), \ldots, x_n(k)]^T \) is the state vector of the fuzzy system. \( A, B, C, D \) is the constant matrix of the appropriate dimension.

The above fuzzy state space model can be physically explained as follows: the entire \( n \)-dimensional state space is divided into \( r \) fuzzy subspace sets, fuzzy direct product sets \( F_j (j = 1, 2, L, n) \), and \( F_j \) is a fuzzy direct product set of \( F_j (j = 1, 2, L, n) \). For each fuzzy subspace, the dynamics of the system can be described by a local linear equation of state, and the overall system dynamics are the weighted sum of these local linear models. The meaning of the T-S fuzzy dynamic model locally expresses the input-output relationship of the nonlinear system. As can be seen from the above system description, the state equation of the whole system is formally approximated by a linear model, but its coefficient matrix \( A, B, C, D \) is a state function, thus essentially describing a nonlinear model.

In general, for a T-S fuzzy control system with \( r \) rules, not all rules are active at any one time, i.e., membership \( h_j > 0, i = 1, 2, \ldots, r \). For a certain rule, it may work at a certain moment, that is, its membership is greater than zero; and at some other moment, it does not work, that is, its membership is equal to zero. Through analysis, it can be found that those rules with membership degree equal to zero have no effect on the current fuzzy control system. Therefore, when analyzing the local stability of the TS fuzzy control system, we can temporarily remove those rules whose membership degree is equal to zero. It is not considered, but only those rules that have a membership greater than zero are considered. In this way, the number of rules to be considered at a certain moment must be less than or equal to the number of rules of the fuzzy system, so it will bring some convenience to the analysis of stability. Based on this, this paper divides the fuzzy interval of the whole fuzzy system into multiple non-overlapping local sub-blur intervals, and defines a certain state input \( x = [x_1, x_2, \ldots, x_n]^T \) for the system [3]. All the rules of activation \( h_j > 0 \) constitute an overlapping rule group. \( x \) is called a point of action for this overlapping rule group. The set of all points of action is called the scope of the overlapping rule group.

3. Robot system structure and kinematics

![Figure 2. Schematic diagram of the position of the wheeled mobile robot.](image)

The motion model of a wheeled robot generally assumes that the wheel is in contact with the ground, and that the contact point is only rolling without relative sliding. It is a typical mathematical model of non-integrity constraint. According to the body structure of the mobile robot and the
principle of the rigid body translation, the mobile robot rotates around the vehicle body at any instant. As shown in Fig. 2, the state of the mobile robot can be represented by the midpoint M of the two drive wheels at the coordinate system position and the heading angle $\theta$. The state of the robot can be represented by the midpoint of its two drive wheels at the position of the coordinate system and the heading angle $\theta$. Let $p = [x, y, \theta]^T$, $q = [v, \omega]^T$, where $x, y$ is the Cartesian coordinates of the centroid of the robot, and $\theta$ is the direction angle, which is the orientation of the robot, which is the angle between the forward direction of the mobile robot and the positive direction of the x-axis, called the heading angle. $v$ and $\omega$ are the center-of-line speed and angular velocity of the wheeled mobile robot respectively, $v_L$ is the linear speed of the left wheel of the mobile robot, $v_R$ is the right wheel speed of the mobile robot, $r$ is the radius of the driving wheel of the robot, and $l$ is the wheel core of the two driving wheels. Straight line distance.

3.1. Robot motion model
Let the driving wheel of the mobile robot have the physical characteristics of pure rolling without sliding, as shown in Fig. 3, so that the mobile robot can only move along the normal direction of the axis of the driving wheel under the non-complete constraint, the system is constrained as follows:

$$y_M \cos \theta - x_M \sin \theta = 0 \quad (3)$$

Therefore, the kinematics equation of the robot is:

$$x' = v \cos \theta$$
$$y' = v \sin \theta$$
$$\theta' = \omega \quad (4)$$

Considering the left-wheel speed $v_L$ and the right-wheel speed $v_R$ of the mobile robot, the physical meaning of the combined mobile robot has the following relationship:

$$\begin{pmatrix} v_L \\ v_R \end{pmatrix} = \begin{pmatrix} 1/r & l/2r \\ 1/r & -l/2r \end{pmatrix} \begin{pmatrix} v \\ \omega \end{pmatrix} \quad (5)$$

Therefore, it can be concluded that the kinematics model of the mobile robot is:

$$\begin{pmatrix} x' \\ y' \\ \theta' \end{pmatrix} = \begin{pmatrix} \frac{r}{2} \cos \theta & \frac{r}{2} \cos \theta \\ \frac{r}{2} \sin \theta & \frac{r}{2} \sin \theta \\ r/l & -r/l \end{pmatrix} \begin{pmatrix} v_L \\ v_R \end{pmatrix} \quad (6)$$
3.2. Wheeled mobile robot dynamics model

Non-finished mobile robots have n-dimensional systems, which can generally be represented by generalized mechanical systems with nonholonomic constraints.

\[
M(q)q'' + V_m(q, q')q + F(q') + G(q) + \tau_d = B(q)\tau - A^T(q)\lambda \\
A(q)q' = 0
\]  

(7)

When we are defining \( M(q) \in R^{nxn} \) is inertia matrix of the system ,and we are defining \( V_m(q, q') \in R^{nxn} \) is the centripetal force ,and we are defining \( F(q') \in R^{nxn} \) is the velocity-dependent of dynamic friction term, \( G(q) \in R^{nx1} \) is the gravity term, \( B(q) \in R^{mxn} \) is the input coefficient matrix, \( \tau \in R^l \) is the control input vector, and \( A(q) \in R^{mxn} \) is the constraint Matrix and constrained reaction, \( \tau_d \) is unknown external interference [4].

For the kinematics model introduced in the previous section, a further kinetic model can be obtained. The wheeled mobile robot is a non-holonomic constraint, and the Lagrangian equation is applied to obtain the dynamic model. The wheeled mobile robot has a motion limit and a horizontal plane, and the potential energy remains unchanged, so here \( G(q) = 0 \). Kinematic models often fail to express all the characteristics of moving people, so here we apply the dynamics model.

\[
S^TMS\ddot{v} + S^T(MS + V_m)'S\ddot{v} + \bar{F} + \tau_d = S^TB\tau
\]  

(8)

When we are defining \( \bar{M}(q) = S^TMS \), \( \bar{V}_m(q, q') = S^T(MS + V_m)'S \), \( \bar{B} = S^TB \), the dynamic is:

\[
\bar{M}(q)\ddot{v} + \bar{V}_m(q, q')\ddot{v} + \bar{F}(v) + \tau_d = \bar{B}\tau
\]  

(9)

4. Robot Fuzzy Control Theory

Due to various reasons in production, it has been caused by manual control of some equipment or production links. The human manual control strategy is formed by the accumulation of long-term practical experience of the operator, which can be described by the natural language of the person, so this control belongs to a language control. While human natural language is ambiguous, this language
control is also called fuzzy language control or simply fuzzy control. From another perspective, fuzzy control is based on fuzzy logic, so it is also called fuzzy logic control [5].

Fuzzy control formalizes and fuzzifiers human experience through fuzzy logic and approximate reasoning, and it becomes a computer-acceptable control model, allowing computers to replace people for effective real-time control. In order to realize fuzzy control, the concept of linguistic variables can be used as a basis for describing manual strategies, and it has evolved into a new type of controller that represents a fuzzy controller. Because it is insensitive to changes in the parameters of the controlled object, it is more robust, and it also facilitates the penetration of people's successful experience to form intelligent control.

4.1. Basic ideas of fuzzy control
In the fuzzy control system, the relationship between input and output is reduced to the conditional statements such as "if A then B" and "if A then B else C", and the input and output theory is obtained by using the method of determining the fuzzy relation. The fuzzy relationship on the domain is then combined with the input and fuzzy relations to obtain an output. The output is generally a fuzzy set, which contains various information of the control quantity. This requires a fuzzy decision and a control quantity is applied to the object. This cycle can make the control process meet the expected requirements. The block diagram of fuzzy control is shown in Figure 4.

![Figure 4. Block diagram of fuzzy control.](image)

Where $S$ represents the set value of the system and is the exact amount. $e, c$ Represents the system deviation and the rate of change of the deviation, both of which are accurate quantities. $E, C$ Represents the amount of blurring in which the deviation and the rate of change of the deviation become after the fuzzy quantization process.

The deviation of the representative fuzzy quantity and the rate of change of the deviation are controlled by the fuzzy control rule. After the approximate reasoning process, the control effect of the fuzzy quantity is obtained. Representing the control effect on the fuzzy quantity, through the fuzzy decision, the precise quantity control of the fuzzy controller output is obtained to control the controlled object.

Through the above brief analysis, the working process of the fuzzy controller is roughly as follows: the controlled quantity is compared with the given value after being converted by the transmitter, and the deviation and deviation change rate are used as the input of the fuzzy decision link after being fuzzified. After the fuzzy decision, the corresponding fuzzy output is obtained, and it is DE fuzzified and converted into an accurate quantity, which is used as the input of the actuator to act on the controlled object, so that the controlled quantity returns to normal.
4.2. T-S fuzzy controller design process

The TS fuzzy controller is based on the data obtained in the control process of the PID controller, and the data is fitted or interpolated by means of a calculation tool to further obtain a direct functional relationship between the input and the output, and the intermediate step is omitted. Directly to the output, the resulting relationship can be used as a control law, that is, the TS fuzzy controller controls the robot model under various working conditions, and the design process is generally divided into the following steps:

1) The robot group is controlled by the PID controller and 36 sets of data about \( e, e_c, u \) are obtained on this basis. This is the design basis of the T-S fuzzy controller. It is necessary to take the data comprehensively and include the maximum and minimum values of \( e, e_c, u \).

2) The above data is processed by interpolation or fitting to obtain an accurate expression of the T-S fuzzy controller. This step relies on MATLAB's powerful data calculation and graphics processing functions to obtain analytical expressions using a variety of different functions. Based on a comprehensive comparison of the effects of each expression control, the best controller is selected.

3) Compare the PID controller with the T-S fuzzy controller, change the robot parameters, and compare the gangs.

4.3. Control characteristics of fuzzy controller and its improvement measures

At present, the PID control strategy commonly used, its integral action reduces the steady-state error, and easily leads to integral saturation, which increases the system overshoot; differential action can improve the response speed, but is particularly sensitive to high-frequency interference, and even leads to the system unstable; the fuzzy control proposed now is a kind of artificial control, which requires some experience. Various methods have their advantages and disadvantages, so fuzzy control is often used in combination with other control methods in system control [6].

In the process of research, in order to adapt to the changing control requirements of the robot speed control system, a new method for designing the TS fuzzy controller is proposed. The TS fuzzy controller design method based on the PID controller knowledge sample. From the PID control of the hydro-generator set speed control system simulation, 36 sets of data samples containing the following control rules are obtained:

\[
if \quad e(k) = x_i \quad and \quad e_c(k) = y_i \quad then \quad u(k) = z_k
\]  

(10)

Through these data, a fuzzy control decision table is established, and then the linear interpolation principle is applied to design a controller that can express fuzzy control rules more accurately. The controller has the following characteristics:

1) This design method can fully draw on the mature experience of conventional PID controller parameter adjustment, making the fuzzy control rule formulation and parameter adjustment easier and more practical.

2) The adjustment quality index is superior to the conventional PID control, which has obvious effects on improving the dynamic response of the system.

3) Because of strong robustness, strong adaptability to the mathematical model of the controlled object, the system has better performance indicators.

The practice shows that the fuzzy control has good dynamic performance and is not sensitive to the changes of the structural parameters of the system. It shows strong robustness. The control process is fast, the inference is simple and reliable, and the fuzzy control rules are between the provisions. The relative independence of the individual rules does not impair the overall situation, so the possibility of error in the entire control logic system is small. In summary, fuzzy control is simpler, more practical, and more adaptable than conventional PID control. However, it still has some shortcomings, such as the presence of static differences and the tendency to generate small-scale oscillations near the industrial control points. The reason is that after E and EC are discretely binned by the quantized link,
part of the information is lost and is not continuous, thus causing the adjustment of the dead zone. To this end, a new control scheme can be proposed, which is a method of online linear interpolation of fuzzy rules. By linearly interpolating the fuzzy control rules, it can overcome the above defects, fundamentally eliminate the quantization error of E and EC, realize the difference of the rotation speed of the robot and the output of the static difference, thereby shortening the adjustment time and significantly improving the dynamics of the system.

5. Experimental simulation

5.1. Simulation Research
In order to verify the feasibility of the obstacle avoidance algorithm, a simulation test program was developed in the MATLAB environment to realize the obstacle avoidance task of the mobile robot. According to the above fuzzy rules, the neural network parameter learning training can be performed, and real-time obstacle avoidance can be completed in the local path planning. The robot performs obstacle avoidance simulation experiments in various experimental environments. The simulation results are shown in Figure 5. The experiments show that the robot can move freely and avoid obstacles to reach the target point.

![Obstacle avoidance simulation results.](image)

Figure 5. Obstacle avoidance simulation results.

5.2. Obstacle avoidance test
Firstly, offline training was conducted, and then an obstacle avoidance test was conducted in a laboratory environment. When a simple regular square obstacle is placed, the result indicates that the collision-free movement of the mobile robot to the target point can be achieved. When there are multiple obstacles or irregular obstacles, because the ultrasonic recognition rate of obstacles is very low, the sensing unit cannot effectively sense the obstacle environment. The system will swing around the robot according to the choice of obstacle avoidance rules. Currently, the mobile robot search path takes a lot of time and is prone to a "deadlock" state, and the probability of robot obstacle avoidance is not great [7].

6. Conclusion
Aiming at the large computational complexity and robustness of the robot fuzzy neural network controller, the T-S fuzzy neural network control method based on hybrid learning algorithm is proposed. Offline genetic optimization and neural network self-learning are used to adjust the parameters of the membership function online, which reduces the computational complexity of the neural network and enhances the robot's ability to respond to environmental changes. By adopting the TS model, the fuzzy operation rules are automatically adjusted by the posterior network, which can
largely eliminate the influence of prior knowledge on the controller, improve the robustness and adaptability of the entire controller, and ensure that even in bad conditions. It can control performance remains at a high level.

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