An Interval Type-2 Fuzzy Neural Network Control on Two-Axis Motion System

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Abstract

In this paper, an interval type-2 fuzzy neural network (IT2FNN) control system is proposed to control a two-axis motion system, which is composed of two permanent magnet linear synchronous motors. The IT2FNN control system, which combines the merits of an interval type-2 fuzzy logic system and a neural network, is developed to approximate an unknown dynamic function. Moreover, adaptive learning algorithms that can train the parameters of the IT2FNN online are derived using the Lyapunov stability theorem. Furthermore, a robust compensator is proposed to confront the uncertainties. To relax the requirement for the value of the lumped uncertainty in the robust controller, an adaptive lumped uncertainty estimation law is also investigated. The proposed control algorithms are implemented. From the simulated and experimental results, the contour tracking performance of the two-axis motion control system is significantly improved and the robustness can be obtained as well using the proposed IT2FNN control system.

Keywords: permanent magnet linear synchronous motors, two-axis motion control system, fuzzy logic system, type-2 fuzzy neural network

1.　Introduction

Permanent magnet linear synchronous motors (PMLSMs) can provide linear motion without using any mechanical interface. They are becoming an alternative solution to rotational motors in many industrial applications, such as transportation and factory automation systems and the packaging industry. However, for the existence of cogging force or detent force in PMLSMs, high performance controller is used to increase the dynamic properties [1-4].

The fuzzy neural networks (FNNs) have the merits such as the capability of fuzzy reasoning to handle uncertain information and the capability of artificial neural networks to learn from processes [5-8]. And thus, it is especially fit for non linear and uncertainty systems. The type-1 FNN was researched in many papers. A type-2 fuzzy neural network (T2FNN) contains two components. A type-2 fuzzy linguistic process is the antecedent part and an interval neural network is the consequent part. The IT2FNN can be adopted to simplify the computational process because the general T2FNN is computationally intensive due to the complexity of the type 2 to type 1 reduction.　Thus, in this paper an IT2FNN of the interval type-2 fuzzy linguistic process and a three-layer interval neural network is proposed.

In this paper, in order to control the PMLSM with high performance, an IT2FNN control strategy is used to control the position of the mover of the two-axis motion control system using two field-oriented control PMLSMs. The mathematic models of PMSLM are deduced. The mechanism of IT2FNN control is introduced. Finally, the control system is constructed and the simulation researches are completed. The research results have been shown that the control system based on the IT2FNN improved the contour tracking performance and the robustness of the two-axis motion control system significantly.

Section 2 presents the model of PMLSM. In Section 3, we research the it2fnn control system. Section 4 proposes the simulated results. Section 5 gives a conclusion to the whole paper.

2. Model of Pmlsm

In a synchronous rotating reference frame the mathematic model of a single-axis PMLSM can be described as the following equation.

$$
\begin{cases}
v_{dt} = R_{wt}i_{dt} + \dot{\psi}_{dt} + \omega_{et}\psi_{qt} \\
v_{qt} = R_{wt}i_{qt} + \dot{\psi}_{qt} + \omega_{et}\psi_{dt} \\
\psi_{dt} = L_{dt}i_{dt} + \psi_{t} \\
\psi_{qt} = L_{qt}i_{qt} \\
\omega_{et} = n\omega_{mt}
\end{cases}
\tag{1}
$$

Where, t is x-axis and y-axis, v_{dt} and v_{qt} are voltages of the d-q axis. i_{dt} and i_{qt} are the currents of the d-q axis. R_{wt} is the phase winding resistance; L_{dt} and L_{qt} are the inductances of the d-q axis. ω_{mt} is the angular velocity of the mover; ω_{et} is the electrical angular velocity; ψ_{t} is the permanent-magnet flux linkage; n is the number of primary pole pairs.

$$
\begin{cases}
\omega_{mt} = \pi v_{m} / \tau \\
v_{et} = n v_{m} = 2\tau f_{et}
\end{cases}
\tag{2}
$$

Where, v_{m} is the linear velocity of the mover; τ is the pole pitch; v_{et} is the electric linear velocity; and f_{et} is the electric frequency. The developed electromagnetic power is given as follow:

$$
P_{t} = F_{t}v_{et} = 1.5n[\psi_{dt}i_{qt} + (L_{dt} - L_{qt})i_{dt}i_{qt}]\omega_{mt}
\tag{3}
$$

Thus, the electromagnetic force is as follow:

$$
F_{t} = 1.5\pi n[\psi_{dt}i_{qt} + (L_{dt} - L_{qt})i_{dt}i_{qt}] / \tau
\tag{4}
$$

The configuration of a single-axis field-oriented control PMLSM servo drive system is shown in Figure 1. The drive system consists of a PMLSM, a ramp comparison current-controlled pulse width modulation (PWM) voltage source inverter (VSI), a field-orientation mechanism, a coordinate translator, a speed control loop, a position control loop, a linear scale, and Hall sensors. The flux position of the PM (θ_{t}) is detected by the Hall sensors (U_{t}, V_{t}, W_{t}) and the mover position signal s_{t}. Different sizes of iron disks can be mounted on the mover of the PMLSM to change the mass of the moving element.

The d_{ct} is the given position command; d_{t} is the feedback position signal. The velocity command v_{ct} can be got when the error between d_{ct} and d_{t} passed through the position loop controller. Then, when the velocity error between the v_{t} linear velocity of the mover and v_{ct} passed through the speed loop controller, the command value of control current i_{cqt} is obtained. The flux current command i_{cdt}=0 control strategy is used to produce the three-phase command currents i_{cat}, i_{cbt}, and i_{cct} by coordinate translator. i_{at} and i_{bt} detected by the sensor are the A and B phase currents. The switching signals of the inverter S_{at}, S_{bt}, and S_{ct} are obtained by the ramp comparison current controller.

Based on the field oriented control system, the electromagnetic force of PMLSM can be expressed as follows:

$$
\begin{cases}
F_{t} = K_{ct}i_{cqt} \\
K_{ct} = 1.5\pi n \psi_{t} / \tau
\end{cases}
\tag{5}
$$

Where, K_{ct} is the coefficient of force to current. The dynamic equation of mover expressed by the electromagnetic force shown in (5) is given by:

$$
F_{t} = m_{t}\dot{v}_{t} + f_{zt}v_{t} + D_{t} + f_{t}(v)
\tag{6}
$$
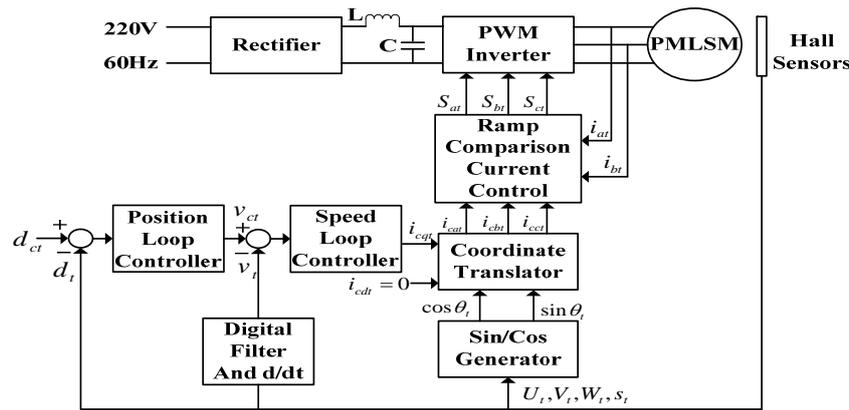
Figure 1. System Configuration of the Field-oriented Control PMLSM Servo Drive

Where, m_t is the total mass of the mover, f_{zt} is the viscous friction coefficient, D_t contains the external disturbances and the cross-coupled interference due to a two-axis mechanism, and $f_t(v)$ is the friction force. Considering the Coulomb friction, the viscous friction, and the Stribeck effect, the friction force can be formulated as follows:

$$f_t(v) = F_{ct}\operatorname{sgn}(v_t) + (F_{st} - F_{ct})e^{-(v_t/v_{st})^2}sng(v_t)$$
$$+ K_{vt}v_t \tag{7}$$

Where, F_{ct} is the Coulomb friction, F_{st} is the static friction, v_{st} is the Stribeck velocity parameter, K_{vt} is the coefficient of viscous friction.

3. IT2FNN Control System

Using type-1 Gaussian membership function (MF), the interval type-2 Gaussian MF is constructed with an adjustable uncertain mean and an adjustable standard deviation. Based on the structure of type-1 if-then rule and the knowledge experts, an interval type-2 fuzzy logic system (FLS) is constructed by the same method. The network structure of the IT2FNN is shown in Figure 2. Each layer of IT2FNN is introduced as follows.

Input Layer: For every node i, the input and the output in this layer are expressed as:

$$\begin{cases} net_i^1 = x_i^1 \\ y_i^1 = f_i^1(net_i^1(N)) = net_i^1(N), \quad i = 1,2 \end{cases} \tag{8}$$

Where, $x_1^1 = d_c - d = e$ is the tracking error between the desired command d_c and the position d of the moving table of the PMLSM, $x_2^1 = \Delta e$ is the tracking error change, and N denotes the number of iterations.

Membership Layer: In this layer, an interval type-2 fuzzy MF is performed by each node. For the jth node, the following equations can be obtained.

$$net_j^2(N) = -0.5(x_i^2 - u_{ij})^2/(\delta_{ij})^2$$
$$y_j^2(N) = f_j^2(net_j^2(N))$$
$$= \begin{cases} y_j^2(N)_u & as \quad u_{ij} = u_{iju} \\ y_j^2(N)_l & as \quad u_{ij} = u_{ijl} \end{cases} \quad j = 1, \cdots g \tag{9}$$

Where, u_{ij} and δ_{ij} are the mean and the standard deviation of the Gaussian function in

the jth term of the ith input linguistic variable x_i^2 to the node of layer 2, respectively. And g is the number of the linguistic values with respect to each input node. Type-2 MFs can be represented as an interval bound by the upper and lower. Thus, the output of the second layer $y_j^2(N)$ is also represented as $y_j^2(N)_u$ and $y_j^2(N)_l$.

Rule Layer: For the kth rule node, the following equations can be obtained.

$$net_k^3(N) = \prod_j w_{jk}^3 x_j^3(N)$$

$$y_k^3(N) = f_k^3(net_k^3(N))$$

$$= \begin{cases} y_k^3(N)_u = \prod_{j=1}^{h} w_{jk}^3 (y_j^2)_u \\ y_k^3(N)_l = \prod_{j=1}^{h} w_{jk}^3 (y_j^2)_l \end{cases} \quad k = 1, \cdots h \qquad (10)$$

Where, x_j^3 is the jth input to the node; In order to simplify the implementation for the real-time control, the weights w_{jk}^3 between the second layer and the third layer and are set to be equal to unity. h is the number of rules. The output of the third layer is expressed as $y_k^2(N)_u$ and $y_k^2(N)_l$ similar to the second layer.
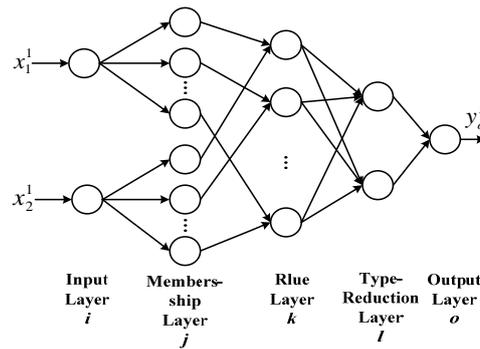
Figure 2. Structure of the IT2FNN

Type-Reduction Layer: In this layer, the type reduction is implemented. The center-of-set type-reduction algorithm is adopted in this IT2FNN. Furthermore, the process of this layer is described as follows:

$$net_l^4(N) = \frac{\sum_{k=1}^{h} w_k^4 y_k^3(N)}{\sum_{k=1}^{n} y_k^3(N)}$$

$$y_l^4(N) = f_l^4(net_l^4(N))$$

$$= \begin{cases} y_{Rl}^4 = \dfrac{\sum_{k=1}^{h} w_{Rk}^4 y_{Rk}^3(N)}{\sum_{k=1}^{h} y_{Rk}^3(N)} = W_R^T Y_R \\ y_{Ll}^4 = \dfrac{\sum_{k=1}^{h} w_{Lk}^4 y_{Lk}^3(N)}{\sum_{k=1}^{h} y_{Lk}^3(N)} == W_L^T Y_L \end{cases}$$

$l=1$ (11)

Where $w_k^4 \in [w_{Rk}^4 \, w_{LK}^4]$ is the centroid of the type-2 interval consequent set, and:

$$W_R = [w_{R1}^4 w_{R2}^4 \cdots w_{Rh}^4]$$

$$Y_R = \left[\frac{y_{R1}^3(N)}{\sum_{k=1}^{h} y_{Rk}^3(N)} \quad \frac{y_{R2}^3(N)}{\sum_{k=1}^{h} y_{Rk}^3(N)} \cdots \frac{y_{Rh}^3(N)}{\sum_{k=1}^{h} y_{Rk}^3(N)} \right]$$

$$W_L = [w_{L1}^4 w_{L2}^4 \cdots w_{Lh}^4]$$

$$Y_L = \left[\frac{y_{L1}^3(N)}{\sum_{k=1}^{h} y_{Lk}^3(N)} \quad \frac{y_{L2}^3(N)}{\sum_{k=1}^{h} y_{Lk}^3(N)} \cdots \frac{y_{Lh}^3(N)}{\sum_{k=1}^{h} y_{Lk}^3(N)} \right]$$

Output Layer: In this layer, the linear combination of y_{Rl}^4 and y_{Ll}^4 is performed.

$$y_o^5 = 0.5(y_{Rl}^4 + y_{Ll}^4) = 0.5(W_R^T Y_R + W_L^T Y_L)$$
$$= 0.5 W^T Y(x^1, u, \delta)$$

(12)

Where $y_o^5 = U_{IT2FNN}$ is the output of the IT2FNN, $W = [W_R^T W_L^T]^T, Y = [Y_R Y_L]^T, x^1 = [x_1^1 x_2^1]$,$u=[u_{11} \ldots u_{1g} u_{21} \ldots u_{2g}]$, and $\delta=[\delta_{11} \ldots \delta_{1g} \delta_{21} \ldots \delta_{2g}]$.

In order to verify the effectiveness of a two-axis motion control system, the IT2FNN control system is proposed. The separate control of x-axis and the y-axis motions are realized. The control system of a single-axis PMLSM based on IT2FNN is shown in Figure 3.
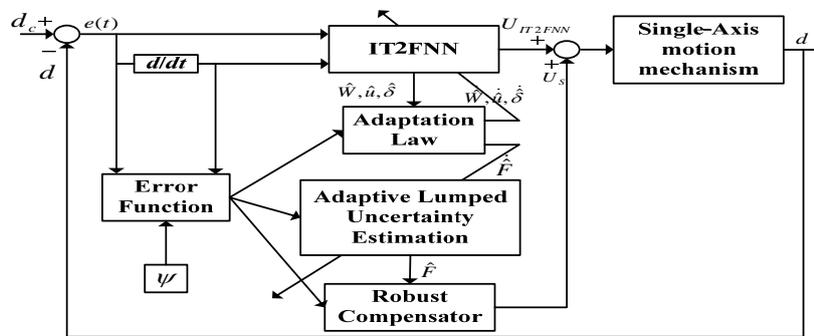
Figure 3. IT2FNN Control System

In order to estimate the unknown dynamic function $L(t)$, the output of the IT2FNN U_{IT2FNN} is put forward by the dynamic equation of mover in PMLSM represented in (6). A robust compensator U_s is used to comparing with the lumped uncertainty F. And thus, the control law of the IT2FNN control system is expressed as:

$$u(t) = U_{IT2FNN} + U_s$$ (13)

The tracking error is defined as $e(t)=d_c-d$ to achieve the control objective, and the error function is expressed as follows:

$$s(t) = \dot{e}(t) + \psi e(t)$$ (14)

where $\psi > 0$.

The adaptive learning algorithms of the IT2FNN are given by (15)–(17), and using the adaptive lumped uncertainty estimation shown in (19), the robust compensator is designed as (18). Thus, the proposed IT2FNN control system is asymptotic stability.

$$\dot{\hat{W}} = 0.5\lambda_1(\hat{Y} - Y_u^T\hat{u} - Y_\delta^T\hat{\delta})s(t) \tag{15}$$

$$\dot{\hat{u}}^T = 0.5\lambda_2\hat{W}^T Y_u^T s(t) \tag{16}$$

$$\dot{\hat{\delta}}^T = 0.5\lambda_3\hat{W}^T Y_\delta^T s(t) \tag{17}$$

$$U_s = \hat{F}(t) \tag{18}$$

$$\dot{\hat{F}}(t) = \lambda_4 s(t) \tag{19}$$

Where, $\hat{W}, \hat{u}, \hat{\delta}$ are the estimation values of the optimal parameters of W, u, and δ in the IT2FNN, s(t) is the error. $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ are positive constants. $\hat{F}(t)$ is an online estimation value of the lumped uncertainty F.

4. Simulated Results

To verify the method proposed in this paper, the simulation research is executed with the MATLAB. The simulation results due to the tracking of four leaves and window contours are given. Moreover, the learning-rate parameters of the weighting interval factor, the mean, and the standard deviation of the IT2FNN controller are given as follows:

$$\lambda_{1x} = 0.09 \quad \lambda_{2x} = 0.04 \quad \lambda_{3x} = 0.02 \quad \lambda_{4x} = 0.05 \quad \psi_x = 1.1 \quad \lambda_{1y} = 0.1 \quad \lambda_{2y} = 0.04 \quad \lambda_{3y} = 0.02 \quad \lambda_{4y} = 0.05 \quad \psi_y = 1.0$$

(a) Control effort of the x-axis   (b) Control effort of the y-axis

(c) Tracking error of the x-axis   (d) Tracking error of the y-axis
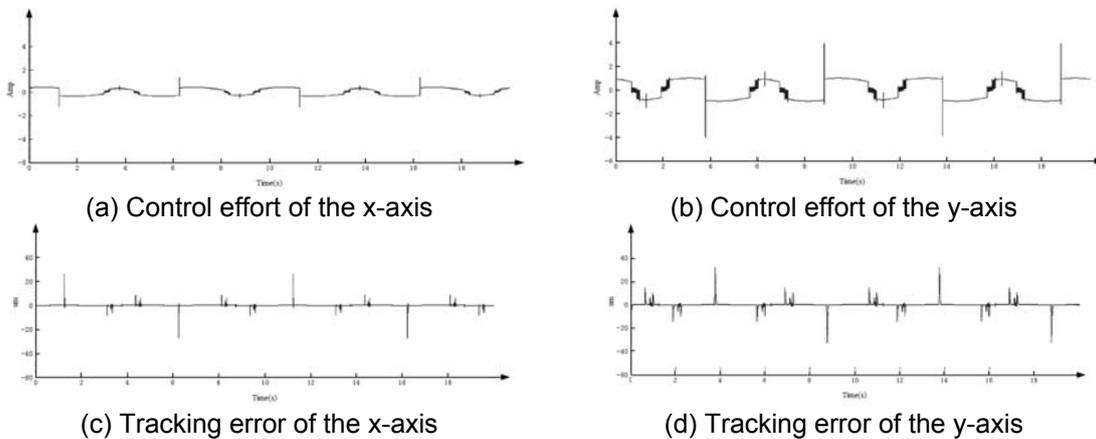
Figure 4. Simulation Results due to the Four Leaves Contour

The simulation results due to the four leaves contour consist of (a) Control effort of the x-axis, (b) Control effort of the y-axis, (c) Tracking error of the x-axis and (d) Tracking error of the y-axis in Figure 4. The simulation results due to the window contour are shown in Figure 5 with the same method. From the simulation results, perfectly tracking responses can be achieved. Furthermore, compared with the parameter variation and the external disturbance, robust control characteristics can be obtained. The effectiveness of control system of IT2FNN is verified.

(a) Control effort of the x-axis

(b) Control effort of the y-axis

(c) Tracking error of the x-axis

(d) Tracking error of the y-axis
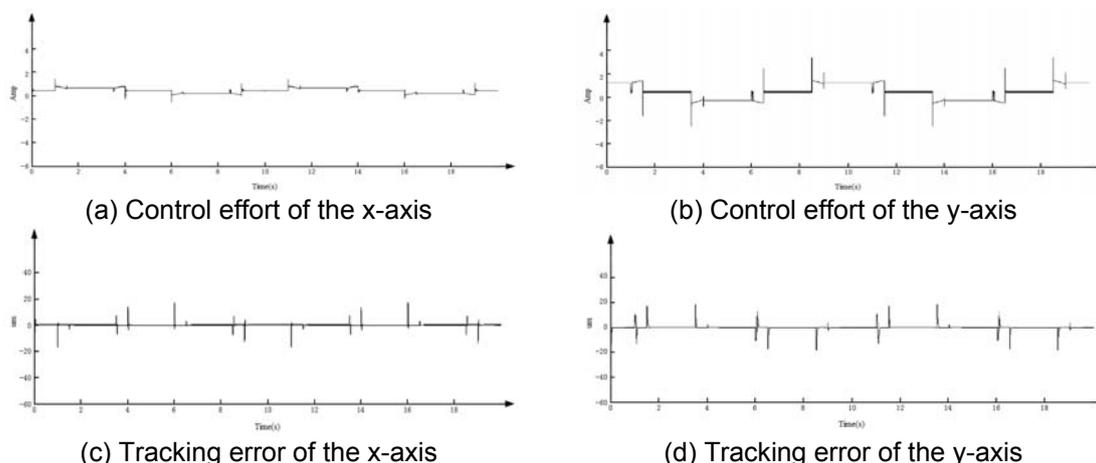
Figure 5. Simulation Results due to the Window Contour

Table 1. Performance Measures of t1fnn and it2fnn Control Systems

| um   Controller | T1FNN | | IT2FNN | |
Tracking Error	Four leaves	window	Four leaves	window
Maximum	40.22	31.57	33.67	18.59
Average	6.26	4.31	3.98	2.08
Standard Deviation	5.15	2.80	3.13	1.44

The T1FNN control system is used to verify the control performance of the IT2FNN control system. Table 1 shows the performance measures of the T1FNN and the IT2FNN control system for the tracking of the four leaves and window contours. Comparing the data in Table 1, the IT2FNN control system possesses improved control performance and is robust with regard to the uncertainties.

5. Conclusion

In this paper, in order to improve the performance of the two-axis motion in PMLSM, the IT2FNN system is used. The mathematic model of PMLSM is deduced. The mechanism of IT2FNN is introduced. To verify the effectiveness of the IT2FNN the simulation system is constructed. The simulation results have shown that the control system with IT2FNN can improve the dynamic performance and the robustness of the PMLSM.

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