Velocity Tracking Control of Wheeled Mobile Robots by Fuzzy Adaptive Iterative Learning Control

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Abstract: In this paper, a fuzzy adaptive iterative learning control (FAILC) strategy is proposed to resolve the trajectory tracking problem of wheeled mobile robots (WMR) based on the dynamic model of WMR and its actuator. In the previous study of WMR trajectory tracking, ILC was usually applied to the WMR kinematical model with the assumption that desired velocity can be tracked immediately. However, this assumption can not be realized in the real world at all. The kinematics model and dynamic model of WMR are deduced in this paper, and a novel iterative learning controller which contains a fuzzy iterative learning component and a feedback component is presented. The controller can work on MIMO systems with variable initial errors. In order to analysis the convergence of the algorithm, the method of Lyapunov-like approach which shows the adjustable parameters of fuzzy system are bounded and tracking errors can converge to zero after initial time as iterative times goes to infinity. Simulation results show the effectiveness of FAILC in the WMR trajectory tracking problem.

Key Words: fuzzy adaptive iterative learning control, wheeled mobile robot, tracking control

1 INTRODUCTION

Nowadays, wheeled mobile robots are treated as a substitute in almost every industry, which can be used in the industrial environment for transportation of materials, inspection and operation for their intelligence, efficiency, flexibility and predictability. Trajectory tracking is one of the most important problems of WMR. Unlike the path following problem, the trajectory tracking problem not only has the spatial position requirements, but also have velocity requirements, i.e., to require the WMR reaching a specific location with specific velocity. Over the past decade, many meaningful research results in this field have emerged. Two kinds of models, i.e., kinematical model and dynamic model, were established, and some control strategies, for example, backstepping control [1], feedback linearization [2], adaptive control [3-5], sliding mode variable structure control [6, 7], fuzzy control [8, 9], neural network control [10, 11], were proposed. Aiming at a class of wheeled mobile robots which usually have the repeated tasks, i.e. relatively fixed trajectory, ILC which has the character of improving the tracking performance by iteration in a fixed time interval can be applied to the WMR trajectory tracking problem. After some years' development, ILC algorithm has been a branch of intelligent control with well-established mathematical description and stability proof, which can handle nonlinear and strong coupling systems in a very simple way and low cost [12-15]. Now, the ILC has made tremendous progress in the learning law, convergence, robustness, learning speed and application, which has been used in industrial robots, rotary systems, heat treat, chemical production processes, etc [12].

The problem of WMR trajectory tracking problem using ILC has received some attention. Early research about ILC and nonholonomic mobile robot was presented in literature [16-18]. Oriolo [16] presented an iterative learning controller applied to nonholonomic mobile robots which can be put in chained form, and the control scheme can obtain nice convergence and robustness properties with respect to modeling inaccuracies as well as disturbances. An ILC technique for path-tracking control for Omni-Directional Vehicle was proposed in [17]. In paper [18], a practical ILC updating law was designed to improve the path following accuracy for an ommi-directional mobile robot. The discrete kinematical model of two-wheeled mobile robot was established in literature [19], and an ILC was applied to implement trajectory tracking for WMR. An ILC algorithm with the analysis of convergence for kinematical model of farm mobile robots was developed in [20]. An improved ILC strategy was developed for path-tracking of a nonholonomic mobile robot in [21]. An ILC law with predictive, current and past learning items to solve the high-precision trajectory tracking issue of WMR was designed in [22].

From the literature review mentioned above, ILC has not been investigated in WMR dynamic model for tracking control. In fact, dynamic model of wheeled mobile robots is more appropriate to real robots than kinetic model. Hence, iterative learning control is proposed to work with the

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dynamic model of wheeled mobile robots in this paper. The main characteristics of the proposed fuzzy adaptive iterative learning control with application to WMR dynamic model are highlighted as follows:

1). A fuzzy adaptive iterative learning control algorithm is incorporated into the WMR dynamic model to improve the tracking performance of the control system. The controller works directly on the dynamic model which is more appropriate than kinematical model.

2). The fuzzy adaptive iterative learning controller contains a fuzzy iterative learning component and a feedback component. The controller can work on MIMO systems with variable initial errors.

This paper is organized as follows. In section 2, the kinematical and dynamic model of WMR is described. In section 3, the fuzzy adaptive iterative learning controller is derived and the convergence of the designed controller is proved. Simulation results are presented in section 4. Finally, conclusions are given in section 5.

2 KINEMATICAL AND DYNAMC MODEL OF WMR

A typical two-wheeled mobile robot is shown in Figure 1. This WMR has two independent driving wheels on the same axis and can move in the coordinate system for the inertial frame OXY. Point C is the center of mass and the center of driving axle of the robot with coordinates (x, y) and heading angle θ. The length of driving axle is $2R$, and the diameter of driving wheels is $2r$. The generalized coordinate vector is defined as $q=[x, y, \theta]^T$.

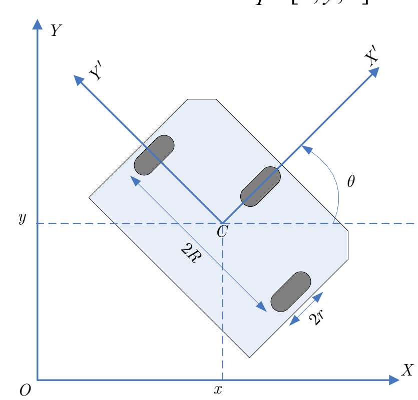

Fig 1. Two-wheeled mobile robot

Suppose that the contact of driving wheels and ground only exists "pure rolling without sliding", the model of two-wheeled mobile robot can be simplified as unicycle-type mobile robot. The nonholonomic constrains of the WMR, which implies that the robot cannot move sideways, is expressed as:

$$\dot{x}\sin\theta - \dot{y}\cos\theta = 0 \tag{1}$$

Eq. (1) can be rewritten as:

$$A^T(q)\dot{q} = [\sin\theta, -\cos\theta, 0]\begin{bmatrix}\dot{x}\\ \dot{y}\\ \dot{\theta}\end{bmatrix} = 0 \tag{2}$$

The linear velocity and angular velocity of WMR in point C are defined as υ and ω respectively. The kinematical model of WMR can be described as:

$$\begin{bmatrix}\dot{x}\\ \dot{y}\\ \dot{\theta}\end{bmatrix} = \begin{bmatrix}\cos\theta & 0\\ \sin\theta & 0\\ 0 & 1\end{bmatrix}\begin{bmatrix}\upsilon\\ \omega\end{bmatrix} \tag{3}$$

Eq. (1) can be rewritten as:

$$\dot{q} = S(q)V \tag{4}$$

where $V=[\upsilon, w]^T$ is the input vector of WMR kinematical model.

According to the Eular-Lagrangian formulation, the dynamic model of WMR is given as:

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) = E(q)\tau + A(q)\lambda \tag{5}$$

where $\dot{q}=[\dot{x}, \dot{y}, \dot{\theta}]^T$ and $\ddot{q}=[\ddot{x}, \ddot{y}, \ddot{\theta}]^T$ are generalized velocity vector and generalized accelerated speed vector, respectively; $M(q)\in\mathbb{R}^{3\times 3}$ is the symmetric positive definite inertia matrix; $C(q,\dot{q})\dot{q}\in\mathbb{R}^3$ is the centripetal and Coriolis force vector; $G(q)\in\mathbb{R}^3$ denotes the gravitational force vector; $E(q)\in\mathbb{R}^{3\times 2}$ denotes input transformation matrix; $\tau=[\tau_L, \tau_R]^T$ is the input torque vector; $A(q)\lambda\in\mathbb{R}^3$ is the constraint forces vector, and λ is the Lagrange multiplier.

When the WMR moves on the plane, its potential remains constant. Considering the WMR mass m and the moment of inertia of WMR I, and ignoring the moment inertia of wheels, the total kinetic energy is $\frac{1}{2}m(\dot{x}^2+\dot{y}^2)+\frac{1}{2}I\dot{\theta}^2$,

$$M(q) = \begin{bmatrix}m & 0 & 0\\ 0 & m & 0\\ 0 & 0 & I\end{bmatrix},$$

$C(q,\dot{q})=0$, $G(q)=0$, $E(q)=\frac{1}{r}\begin{bmatrix}\cos\theta & \cos\theta\\ \sin\theta & \sin\theta\\ -R & R\end{bmatrix}$. Eq. (5) can be rewritten as:

$$M(q)\ddot{q} = E(q)\tau - A(q)\lambda \tag{6}$$

In order to eliminate the Lagrange multiplier in Eq. (6), the derivative of Eq. (4) can be expressed as follows,

$$\ddot{q} = \dot{S}(q)V + S(q)\dot{V} \tag{7}$$

Substituting Eq. (7) into Eq. (6), and multiplying by S^T, we get

$$S^T M\dot{S}V + S^T MS\dot{V} = S^T E\tau - S^T A\lambda \tag{8}$$

where $S^T MS = \begin{bmatrix}m & 0\\ 0 & I\end{bmatrix}$, $S^T M\dot{S}=0$, $S^T E = \frac{1}{r}\begin{bmatrix}1 & 1\\ -R & R\end{bmatrix}$, $S^T A = 0$.

Defining $\bar{M}=S^T MS$, $\bar{B}=S^T E$, Eq.(8) can be simplified as follows:

$$\bar{M}\dot{V} = \bar{B}\tau \tag{9}$$

The robot wheels are driven by DC motors with mechanical gears, and the electrical equation of motor armature is shown as follows:

$$u = L\frac{di}{dt} + R_a i + K_b \omega_m \tag{10}$$

where u, L, R_a, i, ω_m and K_b are input voltage, armature inductance, armature resistance, angle velocity of motor and back electromotive force constant, respectively. If armature inductance is ignored, and the relation between motor torque and armature current ($\tau_M = K_\tau \cdot i$) and relations between torque and angle velocity before gear and after gears ($\tau = n \cdot \tau_m$, $\omega_w = \omega_m / n$) are considered, Eq. (10) can be written as:

$$\begin{bmatrix} \tau_l \\ \tau_r \end{bmatrix} = K_1 \begin{bmatrix} u_l \\ u_r \end{bmatrix} - K_2 \begin{bmatrix} \omega_l \\ \omega_r \end{bmatrix} \tag{11}$$

where $K_1 = nK_\tau / R_a$ and $K_2 = nK_b K_1$.

Considering the relation of velocity vector V and angle velocity of wheels ω_w which is shown as $\begin{bmatrix} \upsilon \\ \omega \end{bmatrix} = \frac{r}{2}\begin{bmatrix} 1 & 1 \\ -1/R & 1/R \end{bmatrix}\begin{bmatrix} \omega_l \\ \omega_r \end{bmatrix}$, we have

$$\begin{bmatrix} \omega_l \\ \omega_r \end{bmatrix} = \frac{1}{r}\begin{bmatrix} 1 & -R \\ 1 & R \end{bmatrix}\begin{bmatrix} \upsilon \\ \omega \end{bmatrix} \tag{12}$$

Substituting Eq. (12) into Eq. (11) , we get

$$\begin{bmatrix} \tau_l \\ \tau_r \end{bmatrix} = K_1 \begin{bmatrix} u_l \\ u_r \end{bmatrix} - \frac{K_2}{r}\begin{bmatrix} 1 & -R \\ 1 & R \end{bmatrix}\begin{bmatrix} \upsilon \\ \omega \end{bmatrix} \tag{13}$$

Then, Substituting Eq. (13) into Eq. (9) , and multiplying by $\bar{M}^{-1}$, we get the dynamic model of WMR combining the DC dynamic model, which is expressed as

$$\begin{aligned} \dot{V} &= -\frac{2K_2}{r^2}\begin{bmatrix} 1/m & 0 \\ 0 & R^2/I \end{bmatrix} V + \frac{K_1}{r}\begin{bmatrix} 1/m & 1/m \\ -R/I & R/I \end{bmatrix} u \\ &= -f(V) + Bu \end{aligned} \tag{14}$$

3 FUZZY ADAPTIVE ITERATIVE LEARNING CONTROLLER DESIGN

In the iteration learning control system, the dynamic model of WMR can be written as:

$$\dot{V}^j(t) = -f(V^j(t)) + Bu^j(t) \tag{15}$$

where $j \in \mathbb{Z}+$ is iteration times, and $t \in [0, T]$.

The tracking problem of WMR is what this paper considers, so the control target is to design a suitable control law to make the velocity $V^j(t) = \begin{bmatrix} \upsilon^j & \omega^j \end{bmatrix}^T$ track the desired velocity $V_d = \begin{bmatrix} \upsilon_d & \omega_d \end{bmatrix}^T$ asymptotically when iteration times trends to infinite. The tracking errors of velocity can be expressed as $e^j = \begin{bmatrix} e_1^j \\ e_2^j \end{bmatrix} = V^j - V_d = \begin{bmatrix} \upsilon^j - \upsilon_d \\ \omega^j - \omega_d \end{bmatrix}$, $e^j \in \mathbb{R}^{2\times1}$, and the derivative of velocity tracking errors are $\dot{e}^j = \dot{V}^j - \dot{V}_d$, $\dot{e}^j \in \mathbb{R}^{2\times1}$.

Define the time-varying boundary layer function as $\phi^j(t) = \begin{bmatrix} \phi_1^j(t) & \phi_2^j(t) \end{bmatrix}^T = \varepsilon^j e^{-kt}$, where $\varepsilon^j = \left| e^j(0) \right| = \begin{bmatrix} \varepsilon_1^j & \varepsilon_2^j \end{bmatrix}^T$ is the absolute value of initial errors in No. j iteration, $\varepsilon_1^j > 0$, $\varepsilon_2^j > 0$, $\varepsilon^j \in \mathbb{R}^{2\times1}$. Obviously , $\phi^j(t)$ is a decreasing function in the iteration period $[0, T]$.

Design the error function as:

$$S_\phi^j(t) = \begin{bmatrix} S_{\phi1}^j(t) \\ S_{\phi2}^j(t) \end{bmatrix} = e^i(t) - S^j(t) \cdot \phi^i(t) \tag{16}$$

where $S^j(t) = \begin{bmatrix} Sat(\frac{e_1^j(t)}{\phi_1^j(t)}) & 0 \\ 0 & Sat(\frac{e_2^j(t)}{\phi_2^j(t)}) \end{bmatrix}$, and $sat(\cdot)$ is saturation function defined as

$$Sat(\frac{e_i^j(t)}{\phi_i^j(t)}) = \begin{cases} 1 \ , & e_i^j(t) > \phi_i^j(t) \\ \frac{e_i^j(t)}{\phi_i^j(t)} \ , & \left| e_i^j(t) \right| \le \phi_i^j(t) \\ -1 \ , & e_i^j(t) < -\phi_i^j(t) \end{cases} \qquad (i = 1, 2)$$

.

According to the definition of saturation function, the error function can be written as $S_{\phi i}^j(t) = \begin{cases} e_i^j(t) - \phi_i^j(t), & e_i^j(t) > \phi_i^j(t) \\ 0, & \left| e_i^j(t) \right| \le \phi_i^j(t) \\ e_i^j(t) + \phi_i^j(t), & e_i^j(t) < -\phi_i^j(t) \end{cases}$. When $S_{\phi i}^j(t) = 0$, $t \in (0, T]$. Because $\phi_i^j(t)$ is a deceasing function along time axis and $\phi_i^j(t)$ will converge to zero rapidly in the condition of large value of k , $\left| e_i^j(t) \right|$ can converge to zero in the time period $(0, T]$. Now, Derive the time derivative of $S_\phi^j(t)^T \cdot S_\phi^j(t)$ as follows:

$$\begin{aligned} &\frac{d}{dt}(S_\phi^j(t)^T \cdot S_\phi^j(t)) = 2S_\phi^j(t)^T \cdot \dot{S}_\phi^j(t) = \begin{cases} 2S_\phi^j(t)^T \cdot (\dot{e}^j(t) - \dot{\phi}^j(t)) \\ 0 \\ 2S_\phi^j(t)^T \cdot (\dot{e}^j(t) + \dot{\phi}^j(t)) \end{cases} \\ &= 2S_\phi^j(t)^T (\dot{e}^j(t) - \begin{bmatrix} sgn(e_1^j(t)) & 0 \\ 0 & sgn(e_2^j(t)) \end{bmatrix} \cdot \dot{\phi}^j(t)) \\ &= 2S_\phi^j(t)^T [-ke^j(t) - sgn(e^j(t)^T)\dot{\phi}^j(t)] \\ &+ 2S_\phi^j(t)^T (\dot{v}^j - \dot{v}_d + ke^j(t)) \\ &= -2kS_\phi^j(t)^T S_\phi^j(t) - 2\left| S_\phi^j(t)^T \right| (k\phi^j(t) + \dot{\phi}^j(t)) \\ &+ 2S_\phi^j(t)^T [Bu - (\dot{V}_d + f(V^j) - ke^j(t))] \\ &= -2kS_\phi^j(t)^T S_\phi^j(t) + 2S_\phi^j(t)^T [Bu - (\dot{V}_d + f(V^j) - ke^j(t))] \end{aligned} \tag{17}$$

If $Bu = \dot{V}_d + f(V^j) - ke^j(t)$, $\frac{d}{dt}(S_\phi^j(t)^T \cdot S_\phi^j(t)) = -2kS_\phi^j(t)^T S_\phi^j(t) \le 0$, which implies that the $S_\phi^j(t)$ is decreasing function, and $S_\phi^j(t)=0$ in the time period $[0,T]$ since $S_\phi^j(0)=0$. Define the unknown nonlinear function $h(X^j(t))=f(V^j)=\begin{bmatrix} h_1(X^j) & h_2(X^j)\end{bmatrix}^T$, where $X^j=\begin{bmatrix} x_1^j & x_2^j\end{bmatrix}^T=[\upsilon^j \quad \omega^j]^T$. The fuzzy technology can be used to design the fuzzy system $\hat{h}_i(X^j(t))$ and approximate the unknown nonlinear function $h_i(X^j(t))$. $\hat{h}_i(X^j(t))$ is described as:

$$\hat{h}_i(X^j(t))=\frac{\sum_{l1=1}^{m1}\sum_{l2=1}^{m2} w_{l1l2}^j \prod_{i=1}^{2}\mu_i^{li}(x_i^j(t))}{\sum_{l1=1}^{m1}\sum_{l2=1}^{m2}\prod_{i=1}^{2}\mu_i^{li}(x_i^j(t))} \tag{18}$$

where $\mu_i^{li}(x_i^j(t))$ is membership function of fuzzy system, w_{l1l2}^j is adaptive parameter, and $m1$ and $m2$ are the number of fuzzy rules of x_1 and x_2. The output vector of fuzzy system is defined as:

$$\hat{h}(x^j)=\begin{bmatrix}\hat{h}_1(X^j)\\ \hat{h}_2(X^j)\end{bmatrix}=\begin{bmatrix}W_1^j(t)^T Z(X^j)\\ W_2^j(t)^T Z(X^j)\end{bmatrix}=W^j(t)^T Z^j(X^j) \tag{19}$$

where $W^j(t)=\begin{bmatrix}W_1^j(t) & W_2^j(t)\end{bmatrix}$ is adaptive parameters vector. Define the optional approximation error as $\varepsilon(X^j(t))=\begin{bmatrix}\varepsilon_1(X^j(t)\\ \varepsilon_2(X^j(t)\end{bmatrix}$, where $\left|\varepsilon_1(X^j(t)\right|\le\varepsilon_1^*$, $\left|\varepsilon_2(X^j(t)\right|\le\varepsilon_2^*$, and $W^*=\begin{bmatrix}W_1^* & W_2^*\end{bmatrix}$ are optional weights, and we have $h(X^j(t))=\hat{h}(X^j(t),W^*)+\varepsilon(X^j(t))$ 。

Define virtual input as $U=Bu-\dot{V}_d+ke^j(t)=U_A+U_B$, $U\in\mathbb{R}^{2\times1}$, and we can get the real input $u=B^{-1}(U+\dot{V}_d-ke^j(t))$ because the input gain matrix B is invertible. U_A and U_B are designed as:

$$U_A=W^j(t)^T Z(X^j)-\theta^j(t) \tag{20}$$

$$U_B=-\frac{\gamma}{2}S_\phi^i(t)(Z(X^j)^T Z(X^j))-\frac{\gamma}{2}S_\phi^i(t) \tag{21}$$

where $\gamma>0$, $\theta^j(t)\in\mathbb{R}^{2\times1}$ denotes approximation error, U_A is the component of fuzzy adaptive iterative learning controller, and U_B is the component of feedback.

In order to ensure the convergence of the controller along with time axis and iteration axis, define the parameter errors as $\widetilde{W}^j(t)=\begin{bmatrix}\widetilde{W}_1^j(t) & \widetilde{W}_2^j(t)\end{bmatrix}^T=W^j(t)-W^*$, $\tilde{\theta}^j(t)=\begin{bmatrix}\tilde{\theta}_1^j(t) & \tilde{\theta}_2^j(t)\end{bmatrix}^T=\theta^j(t)-\theta^*$, where $\theta^*=\begin{bmatrix}\varepsilon_1^* & \varepsilon_2^*\end{bmatrix}^T$.

$$\begin{aligned}
&U-h(X^i)\\
&=u_A+u_B-\hat{h}(X^i(t),W^{*j}(t))-\varepsilon(X^i(t))\\
&W^j(t)^T Z(X^j(t))-\theta^j(t)+u_B-W^{*T}Z(X^j(t))-\varepsilon(X^i(t))\\
&\le\widetilde{W}^j(t)^T Z(X^j(t))+\theta^*-\theta^j(t)+u_B\\
&=\widetilde{W}^j(t)^T Z(X^j(t))-\tilde{\theta}^j(t)+u_B
\end{aligned} \tag{22}$$

Design the adaptive laws of parameters in iteration direction as:

$$\widehat{W}^{j+1}(t)=W_h^j(t)-\gamma S_\phi^j(t)^T Z(X^j(t)) \tag{23}$$

$$\hat{\theta}^{j+1}(t)=\theta^j(t)+\gamma S_\phi^j(t) \tag{24}$$

and

$$\begin{aligned}
W^{j+1}(t)&=proj(\widehat{W}^{j+1}(t))\\
&=\begin{bmatrix} proj(\widehat{W}_{11}^{j+1}(t)) & \ldots & proj(\widehat{W}_{1n}^{j+1}(t))\\ proj(\widehat{W}_{21}^{j+1}(t)) & \ldots & proj(\widehat{W}_{2n}^{j+1}(t))\end{bmatrix}
\end{aligned} \tag{25}$$

$$\theta^{j+1}(t)=\begin{bmatrix} proj(\hat{\theta}_1^{j+1}(t))\\ proj(\hat{\theta}_2^{j+1}(t))\end{bmatrix} \tag{26}$$

where $proj(\cdot)$ is mapping function and defined as:

$$proj(c(t))=\begin{cases}\bar{c} & if\ \ c(t)\ge\bar{c}\\ -\bar{c} & if\ \ c(t)\ge\bar{c}\\ c(t) & otherwise\end{cases},\quad \bar{c}>0.$$

Now, we can state the following result.

Theorem1. Provided that the WMR dynamic model(Eq. 14) satisfies the assumption of known and invertible input gain matrix B, the fuzzy adaptive iterative learning controller (Eq. 20 and Eq. 14) and the parameter adaption laws(Eq. 23-26) are adopt, following conclusions can be obtained.

(1) The parameters of fuzzy system $W^j(t)$, $\theta^j(t)$ are bounded;

(2) Error function $S_\phi^j(t)$ converge to zero when iteration times trends to infinite, i.e. $\lim_{j\to\infty}S_\phi^j(t)=0$;

(3) If k is large enough, $e_i^j(t)$ will converge to zero rapidly after initial time.

4 SIMULATION

In order to demonstrate the effectiveness of the FAILC algorithm, Matlab/Simulink is used for the numerical simulation. Parameters of WMR are as: $m=36kg$, $I=15.625kgm^2$, $2R=1.5m$, $r=0.15m$, $K_1=7.2$, $K_2=2.592$. In this simulation example, the desired velocity trajectories are described by $V_d(t)=\begin{bmatrix}\upsilon_d(t)\\ w_d(t)\end{bmatrix}=\begin{bmatrix}1.2+1.1\sin(t-\pi/2)\\ 0.3\sin(0.4t)\end{bmatrix}$ and $t\in[0,20]$.

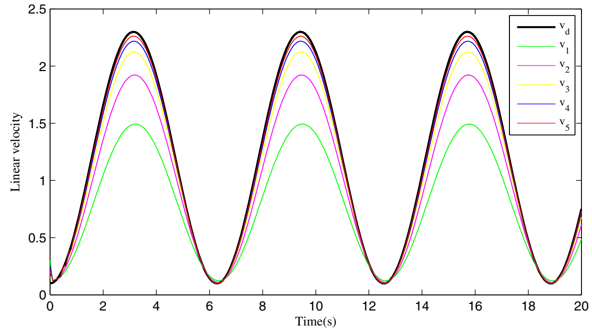

Fig 2. Linear velocity tracking in five times of iterations

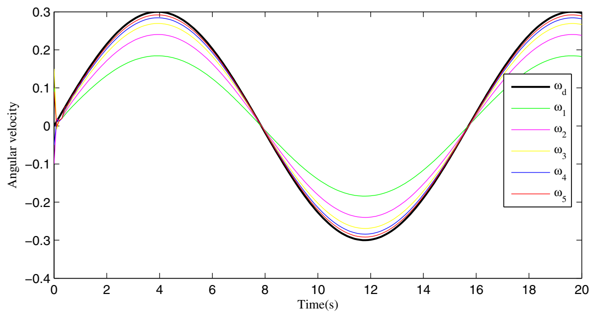

Fig 3. Angular velocity tracking in five times of iterations

In the fuzzy system, we choose Guassian function $\exp\{\frac{(x_i - m_{il})^2}{\sigma_{il}^2}\}$ as membership function, and design seven rules for x_i, i.e. $m1 = m2 = 5$ in Eq.18. The centers of $\hat{h}$ is set as $[m_{11} \cdots m_{15}] = [0, 0.6, 1.2, 1.8, 2.4]$ and $[m_{21} \cdots m_{25}] = [-1, -0.5, 0, 0.5, 1]$, and the variances of $\hat{h}$ is $\sigma_{1l} = 6$ and $\sigma_{2l} = 4$. The initial value of FAILC parameters are set as $W^1(t) = \begin{bmatrix} 0.2 & \ldots & 0.2 \\ 0.2 & \ldots & 0.2 \end{bmatrix}^T$ and $W^1(t) \in \mathbb{R}^{25\times2}$, $\theta^1(t) = [0.2 \quad 0.2]^T$. The value of upper bounder $\bar{c}$ in project function is 25. The varying initial errors $e^j(0)$ come from different initial state $V^j(0)$ which are set as $\left[V^1(0) \cdots V^5(0)\right] = \begin{bmatrix} 0.3 & 0.2 & 0.15 & 0.25 & 0.22 \\ 0.1 & -0.1 & 0.15 & -0.05 & 0.09 \end{bmatrix}$ in five times of iteration. If $k = 8$ and $\gamma = 10$, the velocity tracking trajectories are shown in Figure 2 and Figure 3 which shows the good performance in linear and angular velocity tracking.

5 CONCLUSION

In this paper, the kinematical model and dynamic model of two-wheeled mobile robot are first established, and then the FAILC algorithm for WMR velocity tracking controller which can overcome the variable initial errors in every iteration, is designed. The controller which contains two component (one is a fuzzy iterative learning law and another is feedback law), can work on MIMO model. In order to analysis the convergence of the algorithm, the method of Lyapunov-like approach which shows the adjustable parameters of fuzzy system are bounded and tracking errors can converge to zero after initial time as iterative times goes to infinity. The simulation results verify the effectiveness and convergence of the control laws.

REFERENCES

[1] U. Kumar and N. Sukavanam, "Backstepping based trajectory tracking control of a four wheeled mobile robot," International Journal of Advanced Robotic Systems, vol. 5, pp. 403-410, Dec 2008.

[2] G. Oriolo, A. De Luca, and M. Vendittelli, "WMR control via dynamic feedback linearization: Design, implementation, and experimental validation," IEEE Transactions on Control Systems Technology, vol. 10, pp. 835-852, Nov 2002.

[3] K. Shojaei, A. M. Shahri, A. Tarakameh, and B. Tabibian, "Adaptive trajectory tracking control of a differential drive wheeled mobile robot," Robotica, vol. 29, pp. 391-402, 2011.

[4] C. de Sousa, E. M. Hemerly, and R. K. H. Galvao, "Adaptive control for mobile robot using wavelet networks," IEEE Transactions on Systems Man and Cybernetics Part B-Cybernetics, vol. 32, pp. 493-504, Aug 2002.

[5] R. Barzamini, A. R. Yazdizadeh, and A. H. Rahmani, "A New Adaptive Tracking Control For Wheeled Mobile Robot," in 2006 IEEE Conference on Robotics, Automation and Mechatronics, 2006, pp. 1-6.

[6] N. M. Dung, V. H. Duy, N. T. Phuong, S. B. Kim, and M. S. Oh, "Two-wheeled welding mobile robot for tracking a smooth curved welding path using adaptive sliding-mode control technique," International Journal of Control Automation and Systems, vol. 5, pp. 283-294, Jun 2007.

[7] J. X. Xu, Z. Q. Guo, and T. H. Lee, "Design and Implementation of Integral Sliding-Mode Control on an Underactuated Two-Wheeled Mobile Robot," IEEE Transactions on Industrial Electronics, vol. 61, pp. 3671-3681, Jul 2014.

[8] J. Keighobadi and M. B. Menhaj, "From Nonlinear to Fuzzy Approaches in Trajectory Tracking Control of Wheeled Mobile Robots," Asian Journal of Control, vol. 14, pp. 960–973, 2012.

[9] H. Yu, G.-Y. Tang, H. Su, C.-P. Tian, and J. Zhang, "Trajectory tracking control of wheeled mobile robots via fuzzy approach," in Control Conference (CCC), 2014 33rd Chinese, 2014, pp. 8444-8449.

[10] F. G. Rossomando, C. Soria, and R. Carelli, "Neural network-based compensation control of mobile robots with partially known structure," IET Control Theory and Applications, vol. 6, pp. 1851-1860, Aug 2012.

[11] J. Ye, "Tracking control of a non-holonomic wheeled mobile robot using improved compound cosine function neural networks," International Journal of Control, vol. 88, pp. 364-373, Feb 1 2015

[12] D. A. Bristow, M. Tharayil, and A. G. Alleyne, "A survey of iterative learning control," IEEE Control Systems Magazine, vol. 26, pp. 96-114, Jun 2006.

[13] Y. Q. Wang, F. R. Gao, and F. J. Doyle, "Survey on iterative learning control, repetitive control, and run-to-run control," Journal of Process Control, vol. 19, pp. 1589-1600, Dec 2009.

[14] J.-X. Xu, "A survey on iterative learning control for nonlinear systems," International Journal of Control, vol. 84, pp. 1275-1294, 2011.

[15] C. J. Chien, C. T. Hsu, and C. Y. Yao, "Fuzzy system-based adaptive iterative learning control for nonlinear plants with initial state errors," Ieee Transactions on Fuzzy Systems, vol. 12, pp. 724-732, Oct 2004.

[16] G. Oriolo, "An Iterative Learning Controller for Nonholonomic Mobile Robots," The International Journal of Robotics Research, vol. 17, pp. 954-970, 1998.

[17] K. L. Moore and V. Bahl, "Iterative learning control technique for mobile robot path-tracking control," in Proceedings of the 1999 Mobile Robots XIV, September 20, 1999 - September 22, 1999, Boston, MA, USA, 1999, pp. 240-251.

[18] Y. Q. Chen and K. L. Moore, "Practical iterative learning path-following control of an omni-directional vehicle," Asian Journal of Control, vol. 4, pp. 90-98, 2002.

[19] W. Wu, J. Chen, and L. Mao, "Two-Wheeled Mobile Robot Tracking Based on Iterative Learning Control," in Materials Science and Information Technology, Pts 1-8. vol. 433-440, C. S. Zhang, Ed., ed, 2012, pp. 5866-5870.

[20] X.-H. Bu, Z.-S. Hou, F.-S. Yu, and Z.-Y. Fu, "Iterative learning control for trajectory tracking of farm vehicles," Acta Automatica Sinica, vol. 40, pp. 368-372, 2014.

[21] R. Xi, Y. Li, and X. Xiao, "Trajectory tracking control for a nonholonomic mobile robot using an improved ILC," in 2014 IEEE International Conference on Information and Automation, ICIA 2014, July 28, 2014 - July 30, 2014, Hailar, Hulunbuir, China, 2014, pp. 830-835.

[22] C. Yu and X. Chen, "Trajectory tracking of wheeled mobile robot by adopting iterative learning control with predictive, current, and past learning items," Robotica, vol. 6, pp. 1-22, 2014.