Letter

Data-Driven Active Disturbance Rejection Control of Plant-Protection Unmanned Ground Vehicle Prototype: A Fuzzy Indirect Iterative Learning Approach

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Dear Editor,

This letter proposes a fuzzy indirect iterative learning (FIIL) active disturbance rejection control (ADRC) scheme to address the impact of uncertain factors of plant-protection unmanned ground vehicle (UGV), in which ADRC is a data-driven model-free control algorithm that only relies on the input and output data of the system. Based on the established nonlinear time-varying dynamic model including dynamic load (medicine box), the FIIL technology is adopted to turn the bandwidth and control channel gain online, in which the fuzzy logic system is used to update the gain parameters of iterative learning in real time. Simulation and experiment show the FIIL-ADRC scheme has better control performance.

With the advancement of agricultural intelligence, the artificial spraying method that threatens health is being replaced by the plant protection UGV. The speed and steering angle control of plant protection UGV is particularly important in the process of field operation. The accuracy of steering angle determines whether the UGV needs to be manipulated artificially at the boundary corner of the field [1]. In addition, with the spraying of the liquid, the total mass of the vehicle will be reduced, and the sloshing of the liquid in the medicine box, air resistance, nonlinear friction and the unmodeled part of the system will cause multi-source and unknown interference to UGV. Based on the conditions above, the model of the plant protection UGV is hard to establish. When the model cannot be precise enough, the control effect cannot be further improved, data-driven control schemes can solve this problem [2], [3]. However, the general data-driven control approaches are mostly based on error elimination control methods. When there are unknown external disturbances and internal uncertainties, they cannot predict disturbances well to provide control compensation, and the control effect cannot meet the ideal control requirements. Compared with the general data-driven control approaches, the advantage of ADRC is great when dealing with unknown disturbance, which is more suitable than other model-free data-driven control methods. Therefore, ADRC scheme, a model-free data-driven control method, is used in this letter as basis to control plant protection UGVs. The core idea of ADRC scheme is to treat uncertain factors as total disturbance, and estimate the total disturbance online by the extended state observer (ESO), and compensate the control input [4]. At present, the research on ADRC of UGVs has made some achievements [5].

The values of adjustable parameters can affect the performance of ADRC, it is necessary to select the appropriate parameters based on disturbances [6], [7]. The bandwidth ω_0 affects the observation ability of the ESO, and the control channel gain b_0 is related to system stability and response speed [8]. Taking the variable gain of control channel into account, the adjustment of parameters was fulfilled in [9] by fuzzy logic system. The fuzzy logic system is good at dealing with imprecise system. For example, Chang *et al.* [10] achieved approximation of unknown nonlinear functions based on fuzzy logic systems, and the fuzzy logic fault tolerant control was studied in [11], [12]. In addition, neural network technology is also suitable for solving uncertain system control involving unknown nonlinearity, for example, Sun *et al.* [13] and Liu *et al.* [14] solved the tracking control problem of robot systems based on neural networks. For ADRC scheme, this letter employs two indirect iterative learning controller to independently adjust ω_0 and b_0, which can improve the adaptability of ADRC scheme. Because iterative learning does not rely on the accurate mathematical model of the system, and it could make the system quickly track the expected input, it is widely used in the conditions with repetitive motion characteristics. For example, Preitl *et al.* [15], [16] used an iterative feedback tuning algorithm to optimally tune parameters of controller.

Based on the above exploration, this letter proposes an active disturbance rejection controller based on FIIL control. The novel contributions could be summarized: Firstly, the dynamic model of the plant protection UGV with medicine decrease is established. Secondly, the fuzzy indirect iterative learning is used to optimize the ADRC online, which improve the performance of controller. In addition, the proposed method can be applied to UAVs, unmanned ships, and collaborative control of multiple unmanned systems.

Problem statement: In order to understand the dynamic characteristics of unmanned vehicles and verify the effectiveness of the methods proposed in this letter, it is necessary to establish a dynamic model of unmanned vehicles. Furthermore, it is also necessary to first conduct numerical simulations based on the dynamic model of unmanned vehicles before conducting physical simulations. The plant protection UGV considered in this letter adopts the electric drive mode, which the forward speed is controlled by the driving force generated by the motor on the rear wheel. The medicine box is in the carriage on the rear side of the UGV. The dynamics model of the UGV is (1).

$$\begin{cases} F-F_{d,x}-mg\sin\theta=m\dot{v}_x \\ m(\dot{v}_y+v_x\omega)=K_{\alpha f}(\frac{v_y}{v_x}+\frac{a\omega}{v_x}-\delta)+K_{\alpha r}(\frac{v_y}{v_x}+\frac{b\omega}{v_x}) \\ I_z\dot{\omega}=aK_{\alpha f}(\frac{v_y}{v_x}+\frac{a\omega}{v_x}-\delta)-bK_{\alpha r}(\frac{v_y}{v_x}+\frac{b\omega}{v_x}) \\ \phi=\dot{\omega} \end{cases} \tag{1}$$

where $F_{d,x}=\frac{1}{2TR}C_dA_fP_{abs}(v_x-\omega_x)^2$, F is the sum of the longitudinal forces on the rear wheels, θ is the inclination of the ground, M is the center of gravity of the vehicle, dimensionless, m is the quality of plant protection UGV, g is the acceleration of gravity, v_x is the forward speed, ω_x is the wind speed, v_y is the lateral speed, ϕ is the steering angle, δ is the deflection angle of the front wheel, a is the distance from the center of mass of UGV to the front axle, b is the distance from the center of mass of UGV to the rear axle, R is ideal gas constant, T is ambient air temperature, C_d is coefficient of air resistance, A_f is face area, P_{abs} is absolute air pressure.

Defining the control input $u_1=F$, $u_2=\delta$, we can obtain

$$\dot{v}_x=-\frac{1}{2TRm}C_dA_fP_{abs}(v_x-\omega_x)^2-g\sin\theta+\frac{1}{m}u_1. \tag{2}$$

Defining the UGV control input $u_2=\delta$, one has

$$\begin{cases} \dot{v}_y=\frac{K_{\alpha f}+K_{\alpha r}}{mv_x}+(\frac{aK_{\alpha f}-b}{mv_x}-v_x)\omega-\frac{K_{\alpha f}}{m}u_2 \\ \dot{\omega}=\frac{aK_{\alpha f}-bK_{\alpha r}}{I_zv_x}v_y+\frac{a^2K_{\alpha f}+b^2K_{\alpha r}}{I_zv_x}\omega-\frac{aK_{\alpha f}}{I_z}u_2 \end{cases} \tag{3}$$

where ω is steering angular velocity, $K_{\alpha f}$, $K_{\alpha r}$ are comprehensive lateral stiffness of front and rear wheels, I_z is inertia of UGV.

The medicine box model needs to be considered in the dynamic model. Assuming that the medicine box is a rectangle, one has

$$m(t)=m_0-\rho lwvt \tag{4}$$

where l, w are the length and width of rectangular medicine box, m_0 is the quality of plant protection UGV when loaded with liquid, v is

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rate of uniform drop of liquid level in medicine tank, ρ is density of liquid medicine. By adding the medicine box model, the dynamics model of the plant protection UGV is as follows:

$$\begin{cases} \dot{v}_x = -\dfrac{1}{2TRm}C_dA_fP_{abs}(v_x-\omega_x)^2 - g\sin\theta + \dfrac{1}{m}u_1 \\ \qquad +\rho lw\left[\dfrac{(h-vt)^3}{3}+\dfrac{w^2(h-vt)}{12}\right]+w_1(t) \\ \dot{\omega} = \dfrac{aK_{\alpha f}-bK_{\alpha r}}{I_zv_x}v_y + \dfrac{a^2K_{\alpha f}+b^2K_{\alpha r}}{I_zv_x}\omega - \dfrac{aK_{\alpha f}}{I_z}u_2 \\ \qquad +\rho lw\left[\dfrac{(h-vt)^3}{3}+\dfrac{w^2(h-vt)}{12}\right]+w_2(t) \end{cases} \tag{5}$$

where $w_1(t)$ and $w_2(t)$ are the constructed total non-linearity and interference of the UGV system. It can be seen from (5) that the dynamics model of plant protection UGV studied in this letter is a nonlinear time-varying model.

Controller design: The diagram of the proposed FIIL-ADRC is shown in Fig. 1. The control input is generated by ADRC, in which the bandwidth and gain of ADRC and the learning rate of indirect iterative learning control (ILC) are turning online. Based on the online turning pipeline, ADRC is the basis of the whole controller. The disturbance observation performance is improved by the online turning of the bandwidth of ESO and the controller gain of ADRC. This letter takes the speed control of plant protection unmanned ground vehicle as an example to design the control system. The designed ADRC structure is composed of a tracking differentiator (TD), ESO, and a nonlinear state error feedback control law. The detailed content can be found in [6]. In addition, [6] also includes the process of stability analysis for ADRC. For data-driven model-free control, multiple methods of stability analysis are discussed in [3]. The detailed proof process for the stability analysis of ADRC is presented in [17], and the stability analysis of the iterative learning ADRC can be found in [18]. In order to improve the robustness of the system, this letter employs the ILC to update ω_0 and b_0 in real time. And the mathematical expression of iterative learning is as follows:

$$\dot{x}(t) = f(t,x(t),u(t)),\ \ y(t) = g(t,x(t),u(t)) \tag{6}$$

where $x(t)$ is the system state, $y(t)$ is the system output, $u(t)$ is the control variable of the system.

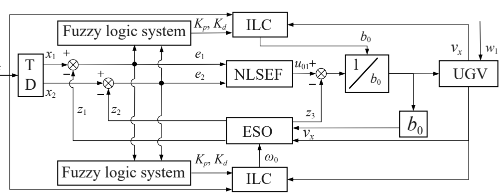


Fig. 1. Control block diagram of ADRC based on fuzzy iterative learning.

Defining the output error as $e_k(t) = y_e(t) - y_k(t)$, the iterative learning algorithm uses the control variable $u_k(t)$ of this round and the system error $e_k(t)$ to generate the control variable of the next round. The following form of PD type learning law is adopted:

$$u_{k+1}(t) = u_k(t) + K_pe_k(t) + K_d\dot{e}_k(t) \tag{7}$$

where K_p, K_d are learning rate.

For indirect iterative learning controller, both the controlled object and the extended state observer can be written in the general form of the state space equation, and there is an expected control u_e

$$\dot{x}_e(t) = f(t,x_e(t)) + Bu_e(t),\ \ y_e(t) = Cx_e(t) \tag{8}$$

where $x_e(t)$ is the excepted system state, $u_e(t)$ is the expected control variable and y_{et} is the expected output.

Theorem: If the system (8) meets the conditions

$$\|I - K_dCB\| \le \bar{\rho} < 1, t \in [0,T] \tag{9}$$

when $k \to \infty$, then $y_k(t) \to y_e(t)$.

Proof:

$$\delta u_{k+1}(t) = \delta u_k(t) - K_pe_k(t) - K_d\dot{e}_k(t) \tag{10}$$

where δu_{k+1} is the difference between the expected control and the actual control.

$$e_k(t) = y_e(t) - y_k(t) = C[x_e(t) - x_k(t)] = C\delta x_k(t) \tag{11}$$

where δx_{k+1} is the difference between the expected state and the actual state.

$$\dot{e}_k(t) = C[f(t,x_e(t)) - f(t,x_k(t)) + B\delta u_k(t)] \tag{12}$$

where $e_k(t)$ is system error. Substituting (11), (12) into (10), one has

$$\begin{aligned} \delta u_{k+1}(t) = {} & [I - K_dCB]\delta u_k(t) - K_pC\delta x_k(t) \\ & - K_dCf(t,x_e(t)) - f(t,x_k(t)). \end{aligned} \tag{13}$$

Then, $P = I - K_dCB$, $Q_k(\delta u_k)(t) = -K_pC\delta x_k(t) - K_dCf(t,x_e(t)) - f(t,x_k(t))$, (13) could be rewritten as

$$\delta u_{k+1}(t) = (P + Q_k)(\delta u(k)) \tag{14}$$

$$\delta x_k(t) = \delta x_k(0) + B\int_0^t \delta u(\tau)d\tau + \int_0^t (f(\tau,x_d(t)) - f(\tau,x_k(t)))d\tau. \tag{15}$$

The norm on both sides of the above equation are took as follows:

$$\|\delta x_k(t)\| \le \|\delta x_k(0)\| + \textstyle\int_0^t (B\|\delta u_k(\tau)\| + N\|\delta x_k(\tau)\|)d\tau \tag{16}$$

where $N > 0$. If $x(t) \le c + \int_0^t (ax(\tau) + by(\tau))d(\tau)$, then $x(t) \le ce^{at} + \int_0^t e^{a(t-\tau)}by(\tau))d(\tau)$, therefore,

$$\|\delta x_k(t)\| \le M_1(b + \int_0^t \|\delta u_k(\tau)\|d\tau) \tag{17}$$

where $M_1 = \max(e^{KfT}, be^{KfT}), b = \sup\|\delta x_k(0)\|$.

For $Q_k(\delta u_k)(t) = -K_pC\delta x_k(t) - K_dCf(t,x_e(t)) - f(t,x_k(t))$ norms on both sides: $\|Q_k(\delta u_k)(t)\| \le M_2(b + \int_0^t \|\delta u_k(\tau)\|d\tau)$. and $M_2 = M_1(h_1c + h_2c_1 + h_2cN)$, $h_1 = \sup\|K_p\|$, $h2 = \sup\|K_d\|$. By norm compatibility: $\|\delta u_{k+1}(t)\| \le \|P + Q_k\|\|\delta u(k)\|$ and $\lim_{k\to+\infty}\|\delta u_{k+1}(t)\| = 0$. Then, from (12), $\lim_{k\to\infty}\|e_{k+1}(t)\| = 0$. ■

Therefore, the designed PD-type learning law iterative learning control algorithm can ensure the system convergence.

In this letter, fuzzy logic system can adjust the learning parameters intelligently and improve the adaptability of the controller. Combining the FIIL controller with the ADRC scheme, it can online tune the bandwidth and control channel gain parameters of the ADRC system. As shown in Fig. 1, the inputs of the fuzzy control system are e_1, e_2, which were come from TD, and the outputs are $\Delta K_p, \Delta K_d$. Seven fuzzy linguistic subsets are defined in each domain:{NB NM NS ZO PS PM PB}. The fuzzy domains of e_1, e_2 are defined as $[-6,6]$ and $[-3,3]$, the fuzzy domains of $\Delta K_p, \Delta K_d$ are $[-0.3,0.3]$. The triangular membership function is adopted as membership function, and the gravity center method is used for defuzzification. The fuzzy output $[C_{\Delta K_p}\ C_{\Delta K_d}]^T$ is defined as follow:

$$[C_{\Delta K_p}\ C_{\Delta K_d}]^T = (A_{e_1} \times B_{e_2})^T \circ R \tag{18}$$

where A_{e_1} and B_{e_2} are the fuzzy sets of e_1 and e_2, R represents the fuzzy rule, T represents the row vector transformation, $\times$ represents a fuzzy implication operator, and $\circ$ is a compositional operator of fuzzy relation. According to the control rules, the final PD-type indirect iterative learning scheme is obtained.

$$\begin{cases} K_p = K_{p0} + \Delta K_p = K_{p0} + defuzzy(C_{\Delta K_p}) \\ K_d = K_{d0} + \Delta K_d = K_{d0} + defuzzy(C_{\Delta K_d}) \end{cases} \tag{19}$$

where K_{p0}, K_{d0} are the initial values of the learning parameters, $defuzzy(\,)$ represents the process of defuzzification.

Based on the adaptive parameters generated by FIILS, the adaptation of the controller was defined as follow:

$$u = f_{ADRC}(\omega_0, b_0) \tag{20}$$

where the ω_0 and b_0 are determined by FIILC, the control input is adjusted adaptively based on the FIIL-ADRC f_{ADRC}.

Numerical simulation: To verify the effectiveness of the proposed control method, a numerical simulation experiment is designed based on the model (1). In order to simulate nonlinear friction and other external and internal disturbances, white noise is added to the input control of UGV, namely $w_1(t)$, $w_2(t)$ in (5). According to physical experiments, the white noise intensity is designed to be 0.5. The simulation results are shown in Figs. 2 and 3. The step signal serves

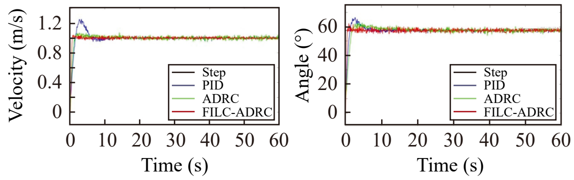
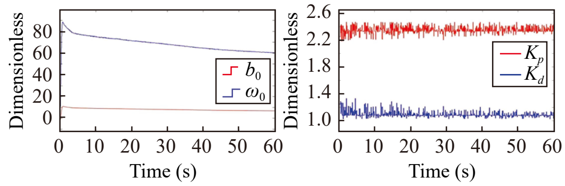


Fig. 2. Simulation results of the proposed method, PID and method in [7].



(a) Online tuning of b_0 and ω_0 (b) Online tuning of K_p and K_d

Fig. 3. Parameters online tuning of FIIL-ADRC.

as a reference signal for the speed and angle of UGV, and the two controllers use the method proposed in this letter, with the rise time is less than 0.6 s and the peak time is less than 1 s, which is stable near the expected speed within 1.5 s. The process of online parameter adjustment through fuzzy indirect iterative learning is shown Fig. 3. Compared to the PID method and the traditional ADRC method in [7], the method proposed in this letter has better control performance.

Experiment: In order to better demonstrate the practicality of the proposed method, real physics experiment is conducted in this letter. The selected UGV prototype is Bingda Nano UGV. The chassis of this UGV is a front wheel steering and rear wheel drive structure and the outdoor conditions of UGV is shown in Fig. 4. Similar to numerical simulation, physical experiments also enable the speed and angle of UGV to track step signals, and the experimental results are shown in Fig. 5, the speed curve of UGV reaches the expected speed after about 1.2 s, and is stable at around 0.9 m/s. The steering response curve of UGV reaches the expected angle in about 0.6 s. After reaching the expected angle, the error between the moments of deviation was controlled within 5°. This letter also compares with traditional ADRC in [7] and verifies that the FIILC-ADRC controller has better control effect under outdoor composite disturbance.

(a) Body tilt between front and rear (b) Body tilt between left and right

Fig. 4. UGV outdoor conditions.

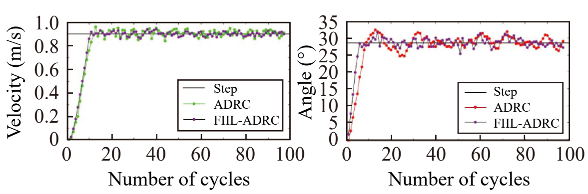


Fig. 5. Experiment results of UGV prototype in field.

Conclusions: Aiming at the interference of longitudinal velocity and lateral steering angle of plant protection UGV, this letter establishes the nonlinear time-varying dynamic model of plant protection UGV including the medicine decrease mode and proposes a fuzzy indirect iterative learning scheme to adjust two important parameters of ADRC online, which further reduced the parameters that need manual tuning in ADRC, and enhanced the practicability and usability of ADRC. Future research will focus on verifying the proposed scheme on a real plant protection UGV. And the proposed method will also be extended to unmanned aerial vehicle systems, ultimately achieving collaborative formation for multiple unmanned systems.

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References

[1] H. Wang, T. Zhang, X. Zhang, and Q. Li, "Observer-based path tracking controller design for autonomous ground vehicles with input saturation," *IEEE/CAA J. Autom. Sinica*, vol. 10, no. 3, pp. 749–761, 2023.

[2] Z.-H. Pang, B. Ma, G.-P. Liu, and Q.-L. Han, "Data-driven adaptive control: An incremental triangular dynamic linearization approach," *IEEE Trans. Circuits and Systems II: Express Briefs*, vol. 69, no. 12, pp. 4949–4953, 2022.

[3] R.-E. Precup, R.-C. Roman, and A. Safaei, *Data-Driven Model-Free Controllers*. Boca Raton, USA: CRC Press, 2021.

[4] J. Han, "From PID to active disturbance rejection control," *IEEE Trans. Industrial Electronics*, vol. 56, no. 3, pp. 900–906, 2009.

[5] H. Wang, Z. Zuo, Y. Wang, H. Yang, and C. Hu, "Longitudinal velocity regulation of UGVs: A composite control approach for acceleration and deceleration," *IEEE Trans. Intelligent Transportation Systems*, vol. 24, no. 10, pp. 11096–11106, 2023.

[6] S. Wang, J. Chen, and X. He, "An adaptive composite disturbance rejection for attitude control of the agricultural quadrotor UAV," *ISA Trans.*, vol. 129, pp. 564–579, 2022.

[7] K. He, C. Dong, and Q. Wang, "Active disturbance rejection control for uncertain nonlinear systems with sporadic measurements," *IEEE/CAA J. Autom. Sinica*, vol. 9, no. 5, pp. 893–906, 2022.

[8] J. Li, X. Qi, H. Wan, and Y. Xia, "Active disturbance rejection control: Theoretical results summary and future researches," *Control Theory & Applications*, vol. 34, no. 3, pp. 281–295, 2017.

[9] O. Castillo, H. Neyoy, J. Soria, P. Melin, and F. Valdez, "A new approach for dynamic fuzzy logic parameter tuning in ant colony optimization and its application in fuzzy control of a mobile robot," *Applied Soft Computing*, vol. 28, pp. 150–159, 2015.

[10] W. Chang, Y. Li, and S. Tong, "Adaptive fuzzy backstepping tracking control for flexible robotic manipulator," *IEEE/CAA J. Autom. Sinica*, vol. 8, no. 12, pp. 1923–1930, 2021.

[11] T. Wu, Z. Yu, and S. Li, "Observer-based adaptive fuzzy quantized fault-tolerant control of nonstrict-feedback nonlinear systems with sensor fault," *IEEE Trans. Fuzzy Systems*, vol. 31, no. 6, pp. 1900–1911, 2023.

[12] M. Van, Y. Sun, S. Mcllvanna, M.-N. Nguyen, M. O. Khyam, and D. Ceglarek, "Adaptive fuzzy fault tolerant control for robot manipulators with fixed-time convergence," *IEEE Trans. Fuzzy Systems*, vol. 31, no. 9, pp. 3210–3219, 2023.

[13] Y. Sun, J. Liu, Y. Gao, Z. Liu, and Y. Zhao, "Adaptive neural tracking control for manipulators with prescribed performance under input saturation," *IEEE/ASME Trans. Mechatronics*, vol. 28, no. 2, pp. 1037–1046, 2023.

[14] Z. Liu, O. Zhang, Y. Gao, Y. Zhao, Y. Sun, and J. Liu, "Adaptive neural network-based fixed-time control for trajectory tracking of robotic systems," *IEEE Trans. Circuits and Systems II: Express Briefs*, vol. 70, no. 1, pp. 241–245, 2023.

[15] S. Preitl, R.-E. Precup, J. Fodor, and B. Bede, "Iterative feedback tuning in fuzzy control systems. theory and applications," *Acta Polytechnica Hungarica*, vol. 3, no. 3, pp. 81–96, 2006.

[16] R.-C. Roman, R.-E. Precup, E.-L. Hedrea, S. Preitl, I. A. Zamfirache, C.-A. Bojan-Dragos, and E. M. Petriu, "Iterative feedback tuning algorithm for tower crane systems," *Procedia Computer Science*, vol. 199, pp. 157–165, 2022.

[17] Q. Zheng, L. Q. Gaol, and Z. Gao, "On stability analysis of active disturbance rejection control for nonlinear time-varying plants with unknown dynamics," in *Proc. 46th IEEE Conf. Decision and Control*, 2007, pp. 3501–3506.

[18] X. Li, S. Tian, and W. Ai, "Active disturbance rejection based iterative learning control," in *Proc. Chinese Control and Decision Conf.*, 2016, pp. 6645–6650.