Research Article

Sensor Fault Diagnosis and Fault Tolerant Control of Quadrotor UAV Based on Genetic Algorithm

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The quadrotor drone is small in size and light in weight, the mechanical structure is simple, and the requirements for the working environment are low. The development of a quadrotor UAV technology is also the focus of the current technical personnel. The author proposes a four-rotor UAV sensor fault diagnosis and fault-tolerant control based on genetic algorithm and introduces common sensor failures, and based on the improved BP neural network of the GA algorithm, the genetic algorithm is improved. This paper uses a classical BP algorithm, a classical GA-BP algorithm, and an improved GA-BP algorithm for training. Using a total of 150 sets of training data and training function using LevenbregMarquardt (trainlm), MeanSquaredError (performance function using mse), in the same noise background, the improved GA-BP algorithm has the highest detection rate, the classical GA-BP algorithm followed, and classical BP algorithm is the worst. Therefore, using the improved GA-BP algorithm, various errors of the sensor can be detected quickly and accurately.

1. Introduction

The quadrotor unmanned aerial vehicle is a kind of direct torque that achieves six degrees of freedom (position and attitude) control and a small UAV system that can take off and land vertically [1]. It is multivariable and nonlinear, has strong coupling and interference sensitivity, and is a multirotor unmanned aerial vehicle with strong maneuverability and simple structure. The micro-multirotor drone has the following advantages: small size and lightweight, low requirements for the working platform and space environment, even the requirements for take-off and landing space are not high [2]. It can be in a relatively small and enclosed space; in order to complete the specified tasks, the flight altitude requirements are low; it can work close to the ground; and the requirements for the working environ-

ment are also low—even if it is complex and harsh, it can work [3]. The mechanical structure design is relatively simple, and the cost of components is low, but it also guarantees a certain degree of reliability [4]. Using it in the fields of military operations and civil aerospace, there is a broad space for development and application [5]. At present, military and commercial use generally choose quadrotor drones; compared with other types of multirotor drones, the mechanical structure design of the four-rotor UAV aircraft is simpler and the volume of the aircraft can be made smaller. And its output control volume is also small; the lift provided by the quadcopter is already enough to bear the general load [6]. Therefore, quadrotor drones can currently play a role in many fields. The development of the quadrotor UAV technology is also the focus of current scientific research workers. It is also one of the hot research issues that
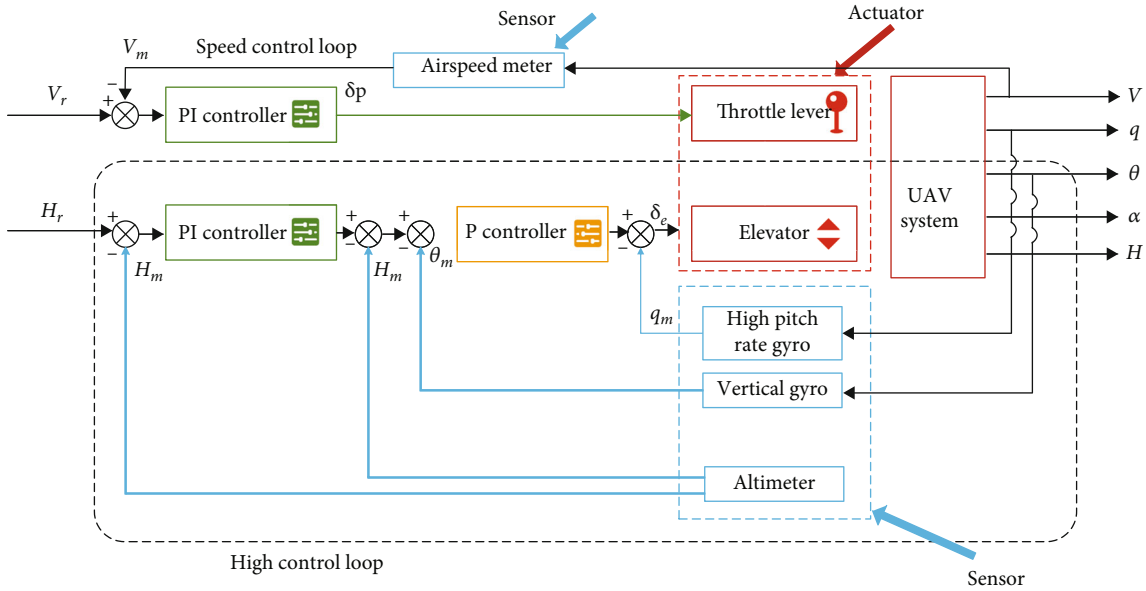
FIGURE 1: Control system fault detection process.

TABLE 1: Comparison of three algorithms.

Algorithm	Target error	Average number of iteration steps
Classic BP	0.01	10
Classic GA-BP	10e-15	17
Improve GA-BP	10e-15	17

FIGURE 2: Convergence curve of a classic BP algorithm.

These two parts can be designed separately in the general system, but they are interdependent on and complement each other. Fault detection and diagnosis are the basis for achieving fault tolerance control [8]. Khil et al. suggested that, in general, some functions of the actuator mechanism that are partially disabled, or have failed completely, are defined as actuator failure. This type of fault is in fault diagnosis and separation research, the most common type of failure. If we follow the severity of its failure, the fault can be further divided into partial failure (the output of the actuator has an error, but there are some basic functions) and completely invalid (the actuator completely loses its original function); that is, regardless of the input signal, the actuator will not make any response [9]. Wang et al. believe that when the sensor cannot output with high precision or outputs wrong data or no data, the performance of these sensors can be considered a sensor failure [10]. Chen et al. believe that according to the degree of impact caused by the failure, it can also be classified as complete failure—that is, the reading of the sensor has nothing to do with the actual status information of the system— and partial failure—that is, the reading deviates from the true state of the system, but its readings still have a certain reference value [11]. Chung et al. in their work on a knowledge-based fault diagnosis method proposed that, due to the characteristics of prior knowledge of the model, it is generally used in the fault diagnosis of offline systems [12]. Yang et al. on the XV215 tilting propeller platform use the extended adaptive neural network for fault diagnosis to test and verified on this basis a nonlinear adaptive controller structure, which can perform fault diagnosis and is very effective [13]. Yang et al.'s paper is based on the analytical model method. Its realization idea can be explained in detail as making full use of existing knowledge in order to build a mathematical model of the system, then pass the input and output of the system to the established mathematical model [14]. Vahidi-

many countries are vigorously developing. A fault detection process for a UAV longitudinal flight control system based on nonlinear adaptive observer is shown in Figure 1 [7].

2. Literature Review

In response to this research question, Peng et al. proposed fault diagnosis and fault-tolerant control: as the name implies, fault diagnosis part and fault tolerance control part.
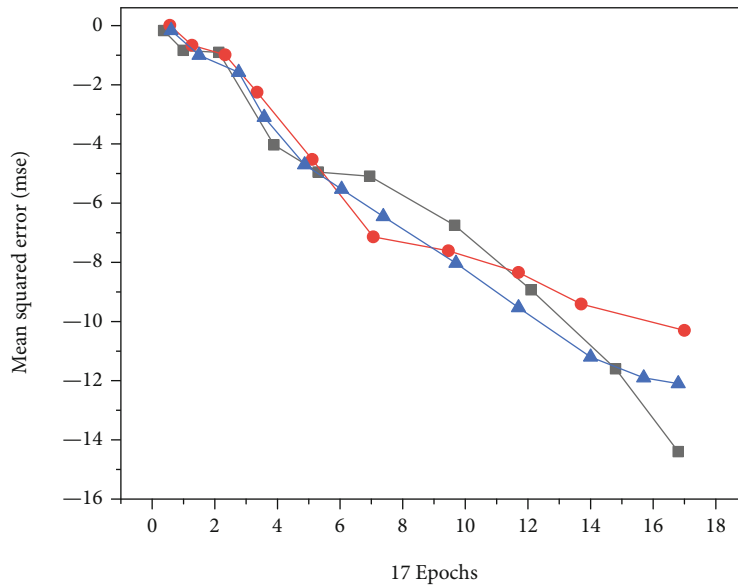
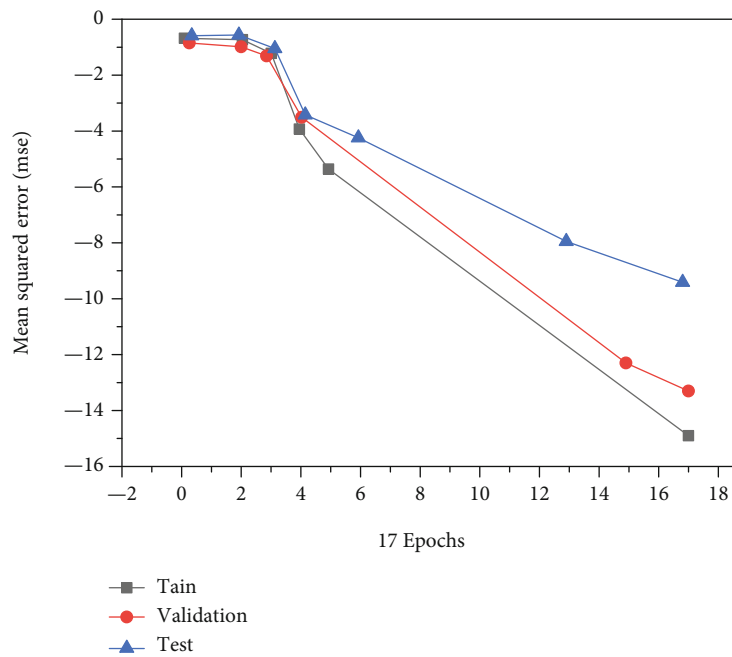FIGURE 3: Convergence curve of a classic GA-BP algorithm.

FIGURE 4: Improved GA-BP algorithm convergence curve.

Moghaddam et al. designed another one for an actuator fault diagnosis based on the analytical model and fault diagnosis method; this method is also based on the Romberg observer residue generation method [15]. Guangming used the Romberg observer residue generation method and applied it to the sensor fault diagnosis of the unmanned helicopter control system. Finally, the method passes simulation and actual flight test and proved that its application in sensor fault diagnosis is effective [16]. Rajeswari and Neduncheliyan also proposed a brand new sensor fault diagnosis method based on the analytical model; this method constructs a set of

full-order unknown observers in order to estimate the local state of the system. Moreover, these local state estimates do not require any local information. Finally, the residual error of the observer is used to detect and reconstruct the fault signal [17]. Nguyen and Ha tested the extended adaptive neural network for fault diagnosis on the XV215 tilt paddle rotor platform and verified that the nonlinear adaptive controller structure can be fault diagnosis and very effective [18]. On the basis of current research, the author proposes a four-rotor UAV sensor fault diagnosis and fault-tolerant control based on genetic algorithm and introduced common sensor
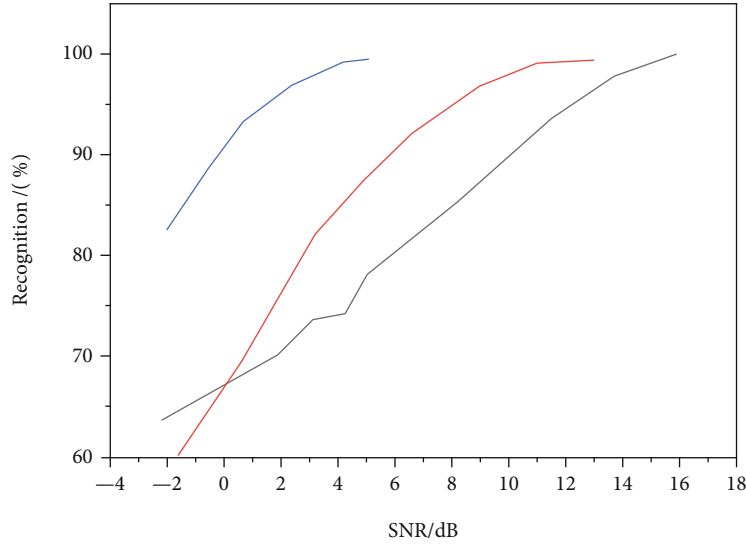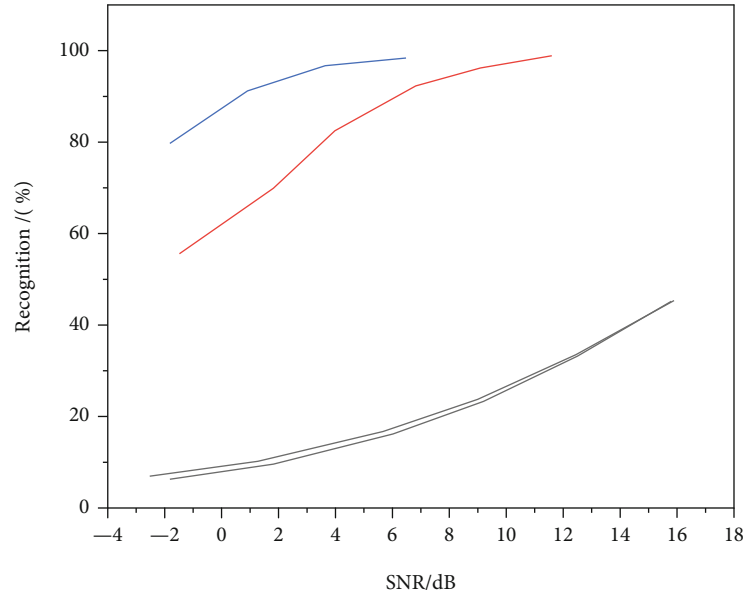
FIGURE 5: Type 1 failure.

FIGURE 6: Type 2 failure.

failures, and based on the improved BP neural network of the GA algorithm, the genetic algorithm is improved. This paper considers the fault of the accelerometer sensor and designs three detection models using MATLAB—the first is the classical BP neural network detection model, the second is the classical GA-BP neural network detection model, and the third is the improved GA-BP neural network detection model—so as to compare the advantages of the three models. The neural network constructed in this paper has three layers: a transmission layer, a hidden layer, and an output layer—100 neurons in the transmission layer, 6 neurons in the hidden layer, and 1 neuron in the output layer. It is very necessary for us to perform fault diagnosis and fault-tolerant control of the actuator mechanism of the quadrotor

UAV: on the one hand, it can improve the safety of the entire quadrotor UAV control system, and on the other hand, it can ensure that the entire quadrotor UAV system is not affected by external environmental factors, maintaining the stability of the system.

3. Methods

3.1. Common Sensor Failures. The main sensor faults studied by the author are sensor stuck, sensor gain change, and sensor constant deviation. Suppose c_{out} is actually output, c_{in} is normal output, and $i = 1, 2, \cdots, m$.

(1) *Failure phenomenon*: this phenomenon is mainly stuck due to the failure of the mechanical parts of the
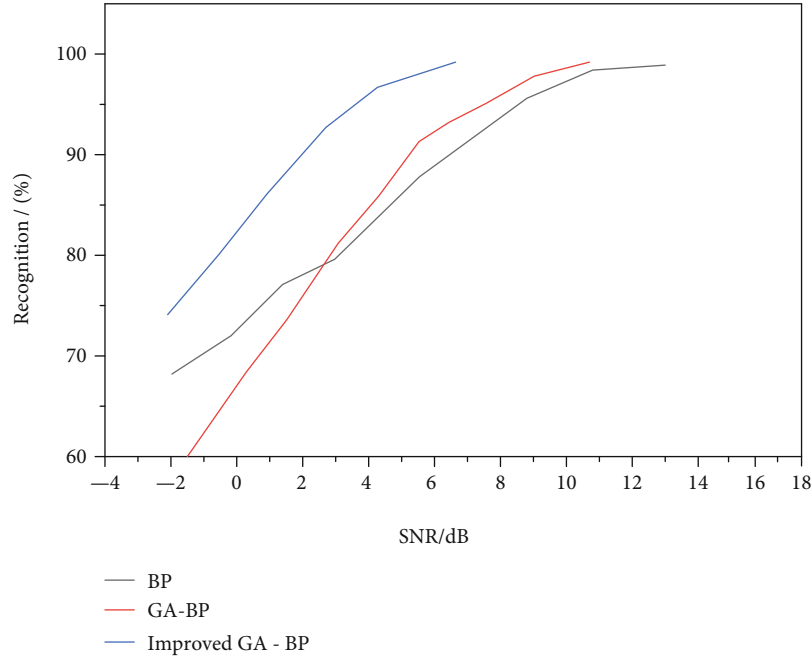
FIGURE 7: Type 3 failure.

actuator or the lack of mechanical lubrication. Regardless of any adjustment and change of the input signal of the actuator, the output of the actuator maintains a fixed value. This failure type will have a serious impact on the stability of the system and is a complete failure fault. The sensor is stuck:

$$c_{iout}(t) = \alpha_i, \tag{1}$$

where a_i is a constant
(2) *Sensor gain change*:

$$c_{iout}(t) = \beta_i c_{in}(t), \tag{2}$$

where β_i is the proportional coefficient of gain change
(3) *Constant deviation of sensor*:

$$c_{iout}(t) = \beta c_{in}(t) + \Delta, \tag{3}$$

where Δ is a constant
(4) *Pine float*: the main sign of failure is that the voltage signal interrupted, resulting in the free deflection of the operating surface and the actuator produces no control force, the output of the actuator is zero, so the propeller stops turning
(5) *Saturate*: the main sign of failure is that the actuator enters saturation after the one-set limit value. The input signal cannot drive the actuator, the actuator is stuck in the limit state of the saturation value, the essence of the time dead failure, which can be described as:

$$u^F(t) = sat(u(t)) \tag{4}$$

(6) *Failure*: the main failure signs are the reduced gain of the actuator, the output control signal is not consistent with the actual situation, the function of the actuator changes compared with the expected situation, and the system control parameter value changes, which leads to the decline of the flight performance of the aircraft. The failure of the deviation also includes constant deviation, drift, and precision damage

3.2. Improved BP Neural Network Based on GA Algorithm. The BP neural network contains an input layer, an output layer, and a hidden layer. The BP algorithm divides the training process into two steps. In the forward operation stage, the signal is transmitted from the loser and the layer to the output layer, reducing the actual value and the expected value to obtain the residual signal. If the error requirement is not met, the residual signal is transmitted from the output layer to the loser layer, and the error is assigned to the connection weights are adjusted according to the error. The BP algorithm is to find the minimum error, using the steepest descent method, the gradient of the error is obtained, and adjust the weight according to its negative gradient direction. In order to illustrate the BP algorithm, first define the error function ε. Subtract the expected output from the actual output, and the squared sum of the difference is used as the error function, then:

$$\varepsilon = \frac{1}{2} \sum_{i=1}^{m} [c_i(t) - \widehat{c}(t)]^2. \tag{5}$$

Among them, $c_i(t)$ is the expected output, and $\widehat{c}_i(t)$ is the $\Delta \omega_{ij}$ actual output.

The BP algorithm adjusts the weight according to the negative gradient direction of the error ε, then the modification amount $\Delta\omega_{ij}$ of weight ω_{ij} is:

$$\Delta\omega_{ij}(n) = -\eta g(n) + \alpha\Delta\omega_{ij}(n-1). \tag{6}$$

Among them, α is the momentum factor, n is the number of iterations, η is the adaptive learning rate, and $g(n)$ is the gradient of the error function to the weight [19].

4. Improved Genetic Algorithm

The basic GA algorithm has a good solution ability for the unimodal function, but the nonlinear problem in practice is very serious, so it is very necessary to improve the algorithm. This paper effectively improves the accuracy of the algorithm by adjusting the coding method while improving parameters such as crossover and variant operator.

4.1. Hybrid Coding Scheme. The advantage of binary coding is simple operation, the search ability is strong, and the real number coding is characterized by high precision and fast efficiency [20]. In this paper, we combine binary and real number coding optimization. This hybrid encoding approach increases the genetic search range while improving the algorithm accuracy.

4.2. Selection of Fitness Function. The fitness value is expressed as:

$$f(X_i) = e(X_i)^{-1}. \tag{7}$$

The objective function is expressed as:

$$e(X_i) = \frac{1}{2n}\sum_{j=1}^{n}\sum_{k=1}^{m}\left(c_{jk} - q_{jk}^{i}\right)^2, \tag{8}$$

where q_{jk}^{i} is the output of the jth node of the kth input, c_{jk} is the expected output, n is the number of training samples, and m is the number of output neurons [21].

4.3. Mixed Selection Operator. The author's selection operation is divided into the following steps: sort by fitness value, then randomly select m samples, and cross and mutate m samples [22]. Keep the best sample of the parent.

4.4. Crossover Operator. When coding real numbers, use an arithmetic crossover operator [23]. The arithmetic crossover operator can be expressed as follows:

$$\left.\begin{array}{l} C_i^1 = P_i^1 + a_i^1\left(P_i^2 - P_i^1\right), i = 1, 2, \cdots, n \\ C_i^2 = P_i^2 + a_i^2\left(P_i^2 - P_i^1\right), i = 1, 2, \cdots, n \end{array}\right\}, \tag{9}$$

where C_i^1, C_i^1 are the individuals after crossover, P_i^1, P_i^2 are the individuals before the crossover, and a_i^1, a_i^2 are random numbers from 0 to 1 [24].

4.5. Mutation Operator. The mutation operation can strengthen the diversity of the population. It is very important to search for the optimal solution. The author uses basic bit mutation operations in binary coding; in real coding, a nonuniform mutation is used [25]. The new gene value x_k' used in the nonuniform mutation is:

$$x_k' = \begin{cases} x_k + \Delta\left(t, U_{\max}^k - \eta_k\right), random(0,1) = 0, \\ x_k - \Delta\left(t, \eta_k - U_{\max}^k\right), random(0,1) = 1, \end{cases} \tag{10}$$

where $\Delta(t, U_{\max}^k)$ is a random number in the range of $[0, U_{\max}^k - \eta_k]$ and $\Delta(t, \eta_k - U_{\max}^k)$ is a random number in the range of $[0, \eta_k - U_{\max}^k]$.

4.6. Crossover Probability and Mutation Probability. In the GA algorithm, crossover probability P_c and mutation probability P_m will affect the convergence of the algorithm; therefore, the choice of P_c and P_m is very important to the algorithm. The author chooses the adaptive crossover and mutation probability:

$$\begin{aligned} P_c &= \begin{cases} \lambda_1\left(f_{\max} - f'\right)/\left(f_{\max} - \bar{f}\right), f' \geq \bar{f}, \\ \lambda_2, f' < \bar{f}, \end{cases} \\ P_m &= \begin{cases} \lambda_3(f_{\max} - f)/\left(f_{\max} - \bar{f}\right), f' \geq \bar{f}, \\ \lambda_4, f' < \bar{f}, \end{cases} \end{aligned} \tag{11}$$

where λ_1, λ_2, λ_3, and λ_4 are constants of 0-1, $f_{\max}$ is the maximum fitness value, 1 is the average value of fitness, $\bar{f}$ is the larger cross fitness value, and f is the fitness value of the variant individual.

5. Results and Analysis

The author considered the failure of the accelerometer sensor. Three detection models are designed using MATLAB: the first is the classic BP neural network detection model, the second type is the classic GA-BP neural network detection model, and the third is the improved GA-BP neural network detection model, in order to compare the pros and cons of the three models. The neural network constructed by the author has 3 layers: the input layer, hidden layer, and output layer, each having 1 layer, and the input layer has 100 neurons, the hidden layer has 6 neurons, and the output layer has 1 neuron.

In this paper, the classical BP algorithm, the classical GA-BP algorithm, and the improved GA-BP algorithm were trained, respectively, with a total of 150 sets of training data, with the training function using LevenbregMarquardt (trainlm), and the performance function using MeanSquaredError (mse). The simulation results are listed in Table 1, and the convergence curves of the three algorithms are shown in Figures 2, 3, and 4.

For the three algorithms, the detection rate can also be used to evaluate the performance of the three methods, the

detection rates of the three methods are shown in Figures 5, 6, and 7.

6. Conclusion

In the quadrotor UAV aircraft system, due to issues such as manufacturing quality, working environment, and its own structure, the actuator mechanism is easy to cause the failure of the actuator mechanism. And as the application of quadrotor drones becomes more popular, the workplace and environment of this work have gradually come into people's lives. Once the actuator mechanism fails, it is very easy to cause fatal errors and hazards to the entire quadrotor UAV system, seriously threatening people's lives and property safety. Therefore, it is very necessary for us to perform fault diagnosis and fault-tolerant control on the actuator mechanism of the quadrotor UAV. On the one hand, it can improve the safety of the entire quadrotor UAV control system; on the other hand, it can ensure that the entire quadrotor UAV system is not affected by external environmental factors, maintaining the stability of the system. In the same background of noise, the improved GA-BP algorithm has the highest detection rate, the classic GA-BP algorithm is second, and the classic BP algorithm is the worst. Therefore, the improved GA-BP algorithm can quickly and accurately detect various errors of the sensor. Response to the failure can be accelerated by designing the failure regulation law in the future.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] B. Gou, X. L. Ge, Y. C. Liu, and X. Y. Feng, "Load-current-based current sensor fault diagnosis and tolerant control scheme for traction inverters," *Electronics Letters*, vol. 52, no. 20, pp. 1717–1719, 2016.

[2] Q. Zhu, Z. Li, X. Tan, D. Xie, and W. Dai, "Sensors fault diagnosis and active fault-tolerant control for pmsm drive systems based on a composite sliding mode observer," *Energies*, vol. 12, no. 9, p. 1695, 2019.

[3] Y. Yong, Y. Zhao, W. Bo, X. Huang, and D. G. Xu, "Current sensor fault diagnosis and tolerant control for vsi-based induction motor drives," *IEEE Transactions on Power Electronics*, vol. 33, no. 5, pp. 4238–4248, 2017.

[4] B. Xian and W. Hao, "Nonlinear robust fault-tolerant control of the tilt trirotor uav under rear servo's stuck fault: theory and experiments," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 4, pp. 2158–2166, 2019.

[5] M. R. Mokhtari, B. Cherki, and A. C. Braham, "Disturbance observer based hierarchical control of coaxial-rotor uav," *ISA Transactions*, vol. 67, no. Complete, pp. 466–475, 2017.

[6] Y. Y. Wang, Y. Sun, C. F. Chang, and Y. Hu, "Model-based fault detection and fault-tolerant control of scr urea injection systems," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 6, pp. 4645–4654, 2016.

[7] V. Yolanda, T. Christian, R. José, and A. Leonardo, "Fault diagnosis and fault-tolerant control of wind turbines via a discrete time controller with a disturbance compensator," *Energies*, vol. 8, no. 5, pp. 4300–4316, 2015.

[8] J. Peng, Z. Hu, J. Liu, S. Yu, and W. Feng, "Fault diagnosis based on chemical sensor data with an active deep neural network," *Sensors*, vol. 16, no. 10, p. 1695, 2016.

[9] S. K. E. Khil, A. B. Youssef, and I. Slama-Belkhodja, "Single phase pwm rectifier sensor fault tolerant control based on residual generation," *Journal of Electrical Systems*, vol. 14, no. 4, p. 190, 2018.

[10] H. Wang, Y. Kang, L. Yao, H. Wang, and Z. Gao, "Fault diagnosis and fault tolerant control for t-s fuzzy stochastic distribution systems subject to sensor and actuator faults," *IEEE Transactions on Fuzzy Systems*, vol. 29, no. 11, pp. 3561–3569, 2020.

[11] W. Chen, H. Xiong, and Zhang, "Design and analysis for early warning of rotor uav based on data-driven dbn," *Electronics*, vol. 8, no. 11, p. 1350, 2019.

[12] W. Chung and H. Son, "Fault-tolerant control of multirotor uavs by control variable elimination," *IEEE/ASME Transactions on Mechatronics*, vol. 25, no. 5, pp. 2513–2522, 2020.

[13] P. Yang, Z. Liu, Y. Wang, and D. Li, "Adaptive sliding mode fault-tolerant control for uncertain systems with time delay," *International Journal of Automation Technology*, vol. 14, no. 2, pp. 337–345, 2020.

[14] F. Yang, X. Peng, L. Zhao, and B. Cui, "Route planning of four rotor uav based on voronoi graph and ant colony algorithm," *Revista de la Facultad de Ingenieria*, vol. 32, no. 3, pp. 531–539, 2017.

[15] A. Vahidi-Moghaddam, A. Rajaei, and M. Ayati, "Disturbance-observer-based fuzzy terminal sliding mode control for mimo uncertain nonlinear systems," *Applied Mathematical Modelling*, vol. 70, no. JUN., pp. 109–127, 2019.

[16] C. Guangming, "Fusion algorithm for information interaction control of multi-uavs based on intelligent algorithm," *International Journal of Computer Applications in Technology*, vol. 61, no. 1/2, p. 107, 2019.

[17] K. Rajeswari and S. Neduncheliyan, "Genetic algorithm based fault tolerant clustering in wireless sensor network," *IET Communications*, vol. 11, no. 12, pp. 1927–1932, 2017.

[18] T. V. Nguyen and C. Ha, "Experimental study of sensor fault-tolerant control for an electro-hydraulic actuator based on a robust nonlinear observer," *Energies*, vol. 12, no. 22, p. 4337, 2019.

[19] Y. J. Zhai, D. L. Yu, K. J. Qian, S. Lee, and N. Theera-Umpon, "A soft sensor-based fault-tolerant control on the air fuel ratio of spark-ignition engines," *Energies*, vol. 10, no. 1, p. 131, 2017.

[20] Y. Du, J. Xia, J. Gong, and X. Hu, "An energy-efficient and fault-tolerant topology control game algorithm for wireless sensor network," *Electronics*, vol. 8, no. 9, p. 1009, 2019.

[21] M. Salehifar, R. S. Arashloo, M. Moreno-Eguilaz, V. Sala, and L. Romeral, "Observer-based open transistor fault diagnosis and fault-tolerant control of five-phase permanent magnet motor drive for application in electric vehicles," *IET Power Electronics*, vol. 8, no. 1, pp. 76–87, 2015.

[22] J. Zhang, G. Rizzoni, A. Cordoba-Arenas, A. Amodio, and B. Aksun-Guvenc, "Model-based diagnosis and fault tolerant control for ensuring torque functional safety of pedal-by-wire systems," *Control Engineering Practice*, vol. 61, pp. 255–269, 2016.

[23] S. Yi, Z. Ping, Z. Yin, M. Wang, and C. Wang, "Open-circuit fault-tolerant control of five-phase pm machine based on reconfiguring maximum round magnetomotive force," *IEEE Transactions on Industrial Electronics*, vol. 66, no. 1, pp. 48–59, 2018.

[24] K. Jeong and S. Choi, "Model-based sensor fault diagnosis of vehicle suspensions with a support vector machine," *International Journal of Automotive Technology*, vol. 20, no. 5, pp. 961–970, 2019.

[25] L. Junjie, H. Jinquan, and L. Feng, "Sensor fault diagnosis for aero engine based on online sequential extreme learning machine with memory principle," *Energies*, vol. 10, no. 1, p. 39, 2017.