Research Article

An Improved Multisensor Self-Adaptive Weighted Fusion Algorithm Based on Discrete Kalman Filtering

Shifen Shao and Kaisheng Zhang

School of Electrical and Control Engineering, Shaanxi University of Science and Technology, Xi'an 710021, Shaanxi, China

Correspondence should be addressed to Kaisheng Zhang; qdhgysfwz@163.com

Received 5 August 2020; Revised 1 September 2020; Accepted 11 September 2020; Published 26 September 2020

Academic Editor: Shubo Wang

Copyright © 2020 Shifen Shao and Kaisheng Zhang. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

When the multisensor self-adaptive weighted fusion algorithm fuses the data sources that were severely interfered by noise, its fusion precision, data smoothness, and algorithm stability will be reduced. To overcome this drawback, the idea was proposed with respect to an improved algorithm which optimized acquisition of fusion data sources with discrete Kalman filtering technique, thus reducing the negative impact on the fusion performance from noise. To verify the effectiveness of the improved algorithm, this paper simulated the fusion process of soil moisture data with fusion samples. The result proved that, under the same circumstance, the improved algorithm has a stronger restrain ability to noise and a better performance in fusion precision, data smoothness, and algorithm stability compared with the general algorithm.

1. Introduction

Multisensor adaptive weight fusion algorithm (or simply as adaptive weight fusion algorithm) is widely used in various measurement occasions as a commonly used data fusion algorithm. Taking obtaining data of various soil moisture from the intelligent water-saving irrigation system as an example [1], the adaptive algorithm [2–12] fused the measuring data (such as humidity and temperature) of several same kinds of sensors [13, 14] to reduce data ambiguity of the individual sensor and improve the confidence level of data. However, the measurement data of the sensor were polluted due to harsh working conditions in the field which caused the affected fusion precision and data smoothness of the conventional adaptive weight fusion algorithm to a certain extent. Aiming at this problem, the paper improves the adaptive weight data fusion algorithm based on discrete Kalman filtering. It was developed by the American Kalman in 1960. It was originally used only for the linear system; after many years, people designed new Kalman filtering theory for the nonlinear system. As the development of the artificial neural network, intelligent algorithm, and information technology, people began to combine to use them. It

is a recursive linear minimum variance estimation method, and it can process the measured values which are only related to some states, so as to obtain the state estimation with the least estimation error [15–17]. As shown in Figure 1, the improved algorithm [17] runs on the host computer system and fuses the raw measurement data (including noise) [18–25] which are sent to the host computer through the ZigBee wireless sensor [26–33] network (ZigBee WSN). The fused data are used as the decision of the irrigation control. Based on this, the irrigation actuator is then driven to perform irrigation operations. The computer simulation result shows that the improved adaptive weight fusion algorithm not only inherits the advantages of all preimproved algorithms but also has stronger noise suppression ability, higher data smoothness, and higher fusion precision than the preimproved algorithm.

2. Discrete Kalman Filtering Algorithm

2.1. Principle of Discrete Kalman Filtering. The soil moisture data [34–38] are converted into digital quantity represented by binary code after D/A conversion and packaged in a ZigBee data frame, and then the data frame is transmitted to

FIGURE 1: Schematic diagram of the intelligent irrigation system.

the host computer through the ZigBee WSN. Due to the limitation of switching frequency and data transmission mode for the D/A converter, it is destined that sampling will only be performed in a series of discrete moments. Therefore, the process of collecting soil moisture data can be abstracted into a discrete process as described in the following:

$$\begin{cases} x_k = \Phi x_{k-1} + w_{k-1} \\ z_k = Hx_k + v_k \end{cases}, \quad (1)$$

where the first equation is the state equation of the data acquisition system, x_k is the system state at time k , and Φ is the system state transition matrix, and Φ is a constant when in the single model. The second equation is the measurement equation, z_k is the measured value at time k , and H is the measurement matrix of the measurement system, and H is a constant when in the single model. w_k is the process noise, and v_k is the measurement noise. In engineering, zero-mean Gaussian white noise is usually applied to simulate v_k and w_k , and the covariance of these two parameters is Q and R , and they are uncorrelated. That is, for all of the following k, j are

$$\begin{aligned} E[w_k] &= 0, E[v_k] = 0, \text{cov}(w_k, w_j) = E[w_k w_j^T] = Q\delta_{kj}, \\ \text{cov}(v_k, v_j) &= E[v_k v_j^T] = R\delta_{kj}, \text{cov}(w_k, v_j) = E[w_k v_j^T] = 0, \\ \delta_{kj} &= \begin{cases} 1, k = j \\ 0, k \neq j \end{cases}. \end{aligned} \quad (2)$$

In the initial state of the measurement system, the statistical characteristics are set as follows: $E(x_0) = \mu_0$, $\text{var}x_0 = E[(x_0 - \mu_0)(x_0 - \mu_0)^T] = p_0$, and $\text{cov}(x_0, w_k) = \text{cov}(x_0, v_k) = 0$. Based on the previous system state, we can get

$$x_{k/k-1} = \Phi x_{k-1/k-1}. \quad (3)$$

$x_{k/k-1}$ is the estimated value of the current system state, and $x_{k-1/k-1}$ is the optimal estimation result of the previous state.

After obtaining the estimated value $x_{k/k-1}$ of the current state in the system, combined with the measured value z_k of the current time, the optimal estimated value $x_{k/k}$ of the current time state of the system is obtained as

$$x_{k/k} = x_{k/k-1} + K_k (Z_k - Hx_{k/k-1}), \quad (4)$$

where K_k is the Kalman gain matrix, which keeps the estimated error variance matrix P_k extremely small. To find K_k , the following formulas are defined:

$$\tilde{x}_{k/k-1} \triangleq x_{k/k-1} - x_k, \quad (5)$$

$$\tilde{x}_{k/k} \triangleq x_{k/k} - x_k. \quad (6)$$

Equation (5) is the system estimation error before the k^{th} measurement data, namely, z_k , are obtained, and equation (6) is the system estimation error after z_k is obtained. Substituting (1) and (5) into (6), the following is obtained:

$$\tilde{x}_k = x_{k/k} - x_k = x_{k/k-1} + K_k (Hx_k + v_k - Hx_{k/k-1}) - x_k = (I - K_k H)\tilde{x}_{k/k-1} + K_k v_k. \quad (7)$$

Then, the variance matrix of the estimated error can be expressed as

$$P_k = E[\tilde{x}_k \tilde{x}_k^T] = E\{(I - K_k H)\tilde{x}_{k/k-1} [\tilde{x}_{k/k-1}^T (I - K_k H)^T + v_k K_k^T] + K_k v_k [\tilde{x}_{k/k-1}^T (I - K_k H)^T + v_k K_k^T]\}. \quad (8)$$

Definition:

$$P_{k/k-1} \triangleq E(\tilde{x}_{k/k-1} \tilde{x}_{k/k-1}^T). \quad (9)$$

The aforementioned definition is the estimated covariance matrix corresponding to $x_{k|k-1}$. Also, because of

$$E[v_k v_k^T] = R, \quad (10)$$

$$E[x_{k/k-1} v_k^T] = E[v_k \tilde{x}_{k/k-1}^T] = 0. \quad (11)$$

Substituting (9)–(11) into (8), the following is obtained:

$$P_k = (I - K_k H) P_{k/k-1} (I - K_k H)^T + K_k P_k K_k^T. \quad (12)$$

Since the purpose of K_k is to minimize the estimated error variance matrix P_k , therefore, P_k can be transformed by formula (12) to

$$\begin{aligned} P_k &= P_{k/k-1} - P_{k/k-1} H^T (H P_{k/k-1} H^T + R_k)^{-1} H P_{k/k-1} \\ &\quad + \left[K_k - P_{k/k-1} H^T (H P_{k/k-1} H^T + R_k)^{-1} \right] \\ &\quad \cdot (H^{T+1} P_{k/k-1} + R_k) \left[K_k - P_{k/k-1} H^T (H P_{k/k-1} H^T + R_k)^{-1} \right]. \end{aligned} \quad (13)$$

It can be known from (13) that if P_k is kept to the minimum, corresponding K_k should be as follows:

$$K_k = P_{k/k-1} H^T (H P_{k/k-1} H^T + R)^{-1}. \quad (14)$$

At this time, the error correlation matrix $P_{k|k}$ used to measure the accuracy of the estimated value can be written as

$$\begin{aligned} P_{k|k} &= P_{k/k-1} - P_{k/k-1} H^T (H P_{k/k-1} H^T + R)^{-1} H P_{k/k-1} \\ &= [I - K_k H] P_{k/k-1}. \end{aligned} \quad (15)$$

Equation (15) is the iterative formula of the error equation. Therefore, from the Kalman filter recursive formula, not only the filter estimation formula can be obtained but also the error analysis can be operated. This is where its advantage lies. If the iterative formula is required to be iterated constantly, the recursive formula of the error correlation matrix $P_{k-1|k-1}$ to $P_{k|k-1}$ corresponding to $x_{k-1|k-1}$ should be obtained. Subtracting x_k from both sides of equation (3), the following is obtained:

$$x_{k/k-1} - x_k = \Phi x_{k-1} - x_k. \quad (16)$$

Substituting (1) and (5) into (16),

$$\tilde{x}_{k/k-1} = \Phi \tilde{x}_{k-1} - w_{k-1}, \quad (17)$$

$$P_{k|k-1} = \Phi P_{k-1|k-1} \Phi^T + Q. \quad (18)$$

In summary, the model of the discrete Kalman filter shown in Figure 2 can be derived.

Based on Figure 2 and according to formulas (3), (4), (14), (15), and (18), the discrete Kalman filter algorithm subroutine module can be programmed on the computer. The program flowchart is shown in Figure 3.

3. Adaptive Weight Fusion Algorithms

3.1. Principle of the Adaptive Weight Fusion Algorithm. Suppose that the same unknown quantity Y is observed by N sensors, and the observation value of each sensor is Y_j ($j = 1, 2, \dots, N$). Then, the observed value of the j th sensor is

$$\hat{Y} = \sum_{j=1}^N W_j Y_j, \quad (19)$$

where W_j is the weight and satisfies

$$\sum_{j=1}^N W_j = 1. \quad (20)$$

The corresponding estimated variance is

$$\sigma^2 = \sum_{j=1}^N W_j^2 \sigma_j^2, \quad (21)$$

where σ_j^2 represents the measurement variance of each sensor. In order to find w_j at the time when the variance in equation (21) reaches a minimum value, the following auxiliary functions are constructed as

$$f(w_1, w_2, \dots, w_N, \lambda) = \sum_{j=1}^N w_j^2 \sigma_j^2 + \lambda \left(\sum_{j=1}^N w_j - 1 \right). \quad (22)$$

For $W_1, W_2, \dots, W_N$ in equation (22), the partial derivatives are, respectively, obtained, and equation (20) is used as the constraint:

$$\begin{cases} \frac{\partial f}{\partial w_1} = 2w_1 \sigma_1^2 + \lambda = 0, \\ \dots \\ \frac{\partial f}{\partial w_N} = 2w_N \sigma_N^2 + \lambda = 0, \\ \sum_{j=1}^N w_j - 1 = 0. \end{cases} \quad (23)$$

After organizing, the following is obtained:

$$\begin{cases} w_1 + w_2 + \dots + w_N = 1, \\ w_j = \frac{u}{\sigma_j^2}, \quad j = 1, 2, 3, \dots; \mu = \frac{\lambda}{2}. \end{cases} \quad (24)$$

Then, the conditional extreme value $\sigma_{\min}^2$ for σ^2 is

$$\begin{aligned} \sigma_{\min}^2 &= \mu \\ &= \frac{1}{\sum_{i=1}^N 1/\sigma_i^2}. \end{aligned} \quad (25)$$

Substituting (25) into (24), the simultaneous equations are

$$w_j = \frac{1}{\sigma_j^2 \sum_{i=1}^N 1/\sigma_i^2}, \quad j = 1, 2, 3, \dots, N. \quad (26)$$

FIGURE 2: Discrete Kalman filter model.

FIGURE 3: Discrete Kalman filter algorithm subroutine flowchart.

The above estimation process for the true value Y is based on all of the measurement data obtained by N sensors in a single measurement process. When the state of the measured object remains relatively constant for a certain period of time, in order to improve the estimation accuracy, when the k^{th} estimation of the true value Y is performed, the average value of the previous measurement data for k times may be used:

$$\bar{Y}_j(k) = \frac{1}{k} \sum_{i=1}^k Y_j(i), \quad j = 1, 2, 3, \dots, N. \quad (27)$$

To make estimation, the estimation equation can be written as follows:

$$\hat{\bar{Y}} = \sum_{j=1}^N w_j \bar{Y}_j(k). \quad (28)$$

Since $\bar{Y}_j$ is an unbiased estimation of Y , it is also an unbiased estimate of Y . The estimated total variance at this time is

$$\bar{\sigma}^2 = E[Y - \hat{\bar{Y}}^2] = E\left[\sum_{j=1}^N w_j^2 (Y - \bar{Y}_j(k))^2\right] = \frac{1}{k} \sum_{j=1}^N w_j \sigma_j^2. \quad (29)$$

The same as the solution process of $\sigma_{\min}^2$, the conditional extreme values are

$$\bar{\sigma}_{\min}^2 = \frac{1}{k \left(\sum_{i=1}^N 1/\sigma_i^2 \right)} = \frac{\sigma_{\min}^2}{k}. \quad (30)$$

From (30), it can be concluded that, as the number of measurement k increases, the overall variance of the true value Y estimation will become smaller, thereby achieving the purpose of estimation accuracy improvement.

3.2. Calculation Method of σ_j^2 . Since the optimal weighting factor w_j is determined by the variance σ_j^2 of each sensor, σ_j^2 is generally not known, so it is necessary to indirectly pass the measured values provided by the sensors, and find it according to the following algorithm. There are any two different sensors i and j , in which the measured values are Y_i and Y_j , respectively, and the corresponding observation errors are n_i, n_j , that is, $Y_i = Y + n_i$ and $Y_j = Y + n_j$. Because the mean value of n_i, n_j is zero and is not related to each other and is not related to Y , Y_j is the autocorrelation coefficient R_{jj} , and the correlation coefficient R_{ij} between Y_i and Y_j , respectively, satisfies

$$\begin{aligned} R_{jj} &= E[Y_j Y_j] \\ &= E[Y^2] + E[n_j^2], \end{aligned} \quad (31)$$

$$\begin{aligned} R_{ij} &= E[Y_i Y_j] \\ &= E[Y^2]. \end{aligned} \quad (32)$$

Substituting (31) into (32),

$$\begin{aligned} \sigma_j^2 &= E[n_j^2] \\ &= R_{jj} \\ &= R_{ij}. \end{aligned} \quad (33)$$

For the calculation of R_{jj} and R_{ij} , they can be solved by the time-domain estimation: set $R_{jj}(k)$ as the time-domain estimation value of R_{jj} at time k and $R_{ij}(k)$ as the time-domain estimation value of R_{ij} at time k ; then,

$$R_{jj}(k) = \frac{1}{k} \sum_{m=1}^k Y_j(m)Y_j(m), \quad (34)$$

$$R_{ij}(k) = \frac{1}{k} \sum_{m=1}^k Y_i(m)Y_j(m).$$

To reduce the error, the average value of $R_{ij}(k)$, namely $\bar{R}_{ij}(k)$, is usually taken instead of $R_{ij}(k)$:

$$\bar{R}_{ij}(k) = \frac{1}{N-1} \sum_{i=1, i \neq j}^N R_{ij}(k). \quad (35)$$

Substituting (32) into (35),

$$\sigma_j^2(k) = R_{jj}(k) - \bar{R}_{ij}(k). \quad (36)$$

4. Improvement of the Adaptive Weight Fusion Algorithm

4.1. Drawbacks of the Current Algorithms. It is not difficult to conclude from (25), (26), and (30) that both of the conditional extremes of the estimation error and the sensor weights are closely related to the measurement variance of the sensor. The smaller the sensor measurement variance is, the smaller the conditional extreme of the error is estimated and the larger the corresponding sensor weight is, which reflect the characteristics that the sensor weight is autoadaptive to the sensor measurement variance. However, it is precisely because of the direct impact of the sensor measurement variance on these parameters; if the sensor measurement variance has frequent and severe jitter, the corresponding sensor weight will certainly have jitter, which will finally affect the effect of data fusion.

Taking the measurement of soil moisture as an example, three humidity sensors are provided to simultaneously measure soil moisture in a certain area, and the true value of soil moisture in this area is set as 21RH% (constantly considered to be constant in a certain period of time). Based on this true value, Gaussian white noise with a mean value of 0 and variances of 0.2, 0.5, and 0.7 was added to simulate different levels of noise pollution of the three sensors, and 100 fusion processes were simulated on a computer.

As shown in Figure 4, because the autoadaptive weight fusion algorithm before improvement directly uses the raw

measurement data of the noise-contaminated sensor as its fusion data source, the measurement variance of the sensor will experience severe jitter caused by a small sample size (sample capacity is less than 15). After this severe jitter, there is still a relatively frequent small jitter, which further leads to the frequent and random jitter of the corresponding sensor weight curve in Figure 5 within a certain range. Although this kind of sensor weight jitter reflects the dynamic adjustment characteristic of sensor weight according to the sensor measurement variance by the autoadaptive weight fusion algorithm, too much jitter will eventually affect the fusion effect. As shown in Figure 6, the frequent and irregular sensor weight jitter makes smoothness decrease the smoothed data. The data curve has more glitch, and the convergence speed is slower (the fusion curve in the figure becomes flat after 60 times of fusion).

4.2. Improved Autoadaptive Weight Fusion Algorithm. It can be found from the analysis in Section 4.1 that the main reason for this drawback is that the fusion data source used by the algorithm contains a lot of noise that affect the measurement variance of the sensor. Moreover, in the fusion process, the noise which was contained in the fused data source has not been processed. It shows that the sensor measurement variance shown in Figure 4 always shakes around a certain value without significant drop after entering a relatively stable phase. If the noise in the data source can be suppressed to a certain extent, the sensor measurement variance σ_j^2 will decrease. It can be known from equations (25) and (30) that the decrease of σ_j^2 eventually causes the conditional extreme value $\bar{\sigma}_{\min}^2$ of the overall estimated variance to decrease, and with the increase in the number of estimates k , the trend of this decline will become more apparent.

Considering that the core of the discrete Kalman filtering algorithm consists of only five formulas and the algorithm logic is clear (shown in Figure 3), it is easy to be programmed by the computer. It also has advantages of rapid convergence, good stability, high precision, and low program memory overhead. Therefore, the discrete Kalman filtering algorithm can be used as an ideal data preprocessing method. The original measurement data sent by the data acquisition terminal to the host computer are filtered as follows.

Set the j th ($j = 1, 2, \dots, N$) sensor of the N sensors at time k ($k \geq 1$) to have the original measured value as $Y_j(k)$, the initial estimated value of the filtering algorithm as $\tilde{Y}_j(0)$, and the filtered output value as $\tilde{Y}_j(k)$; then, the discrete Kalman filter formula can be written as

$$\begin{aligned} \{ Y_j(k)_{k/k-1} = \Phi \tilde{Y}_j(k-1), P_{k/k-1} = \Phi P_{k-1/k-1} \Phi^T + Q, K_k = P_{k/k-1} H^T (H P_{k/k-1} H^T + R)^{-1}, \tilde{Y}_j(k) = Y_j(k)_{k/k-1} + K_k [Y_j(k) - H Y_j(k)_{k/k-1}], \\ P_{k/k} = [I - K_k H] P_{k/k-1}. \end{aligned} \quad (37)$$

FIGURE 4: Variance changing curve of the data source before improvement.

FIGURE 5: Weight curve of the sensor before improvement.

FIGURE 6: Fusion effect of the algorithm before improvement.

According to the flowchart shown in Figure 3, after the calculations of equation (37), $\{\tilde{Y}_j(k)\}$ ($j = 1, 2, \dots, N; k = 1, 2$, and 3) is used as the fusion data source of autoadaptive weight fusion to replace the original $\{Y_j(k)\}$, thus achieving the purpose of suppressing the noise and reducing σ_j^2 . The improved fusion algorithm is shown in Figure 7.

FIGURE 7: Flowchart of the improved autoadaptive weight fusion algorithm.

5. Simulation and Analysis of Improved Algorithms

As described in Section 4.1, there were 3 humidity sensors (type: RS485) to measure soil moisture in a certain area at the same time. The true value of soil moisture at this moment was set to 21RH% (can be considered constant in a certain period of time), and based on this, true value Gaussian white noise (white noise launcher type: Noisecom NC6000A/NC8000A) with a mean of zero and a variance of 0.2, 0.5, and 0.7 was added, respectively, to simulate the noise pollution of

FIGURE 8: Variance curve of the filtered fusion data source.

TABLE 1: Initial parameters of the discrete Kalman filter.

Unit	Initial estimation variance, $P_{0 0}$	Initial estimate, $x_{0 0}$	Process variance, Q
Sensor 1	0.6	19	$4e-4$
Sensor 2	0.6	20	$4e-4$
Sensor 3	0.6	23	$4e-4$

the sensor. A total of three sets of measurements were generated, and every group contained 100 times of measurements. Then, discrete Kalman filtering was used for the three sets of measured values, and the three sets of filtered measured values were used as the data source of the autoadaptive weight fusion algorithm, and the variance of the filtered measured data (fused data source) is as shown in Figure 8. The initial parameters of the discrete Kalman filtering algorithm (see Table 1) can be determined from experimental data. The sensor weight curve and the fusion output curve of the improved algorithm are shown in Figures 9 and 10.

As shown in Figure 8, at the beginning of the discrete Kalman filtering algorithm, compared with the variance of the measured values of the prefiltered sensors (see Figure 4), the variance of the measured values of the three groups of sensors is significantly reduced after filtration, and the variance can be controlled relatively faster and maintained at a lower level (after about 30 filtering, the variance is below 0.1). This indicates that the noise contained in the sensor raw data is significantly suppressed. Therefore, using the filtered three sets of sensor measurements as the fused data source of the autoadaptive weight fusion algorithm will significantly reduce σ_j^2 ($j = 1, 2, \text{ and } 3$). Moreover, since the variance curve of the measured value from the filtered sensor becomes smoother with the increase of the number of filtration times, the linkage effect on the sensor weight and the fused output caused by the frequent jitter of the sensor variance can be better avoided. As shown in Figure 9, the improved algorithm has better suppression ability for the sensor weight jitter: after 15 fusions on average, the weight of each sensor has no obvious jitter, which avoids the influence on fusion precision due to frequent jitter of sensor weight and thus significantly improves the fusion accuracy and convergence speed. As shown in Figure 10, after about 35 fusions, the fusion output is already stable and extremely close to the true

FIGURE 9: Sensor weight curve of the improved algorithm.

FIGURE 10: Fusion output curve of the improved algorithm.

value, and the fused output curve has fairly high smoothness and substantially no jitter occurrence. This improved algorithm is significantly better than the algorithm before improvement shown in Figure 6.

6. Conclusion

The paper uses the discrete Kalman filtering algorithm to improve the acquisition approach of the fusion data source in the autoadaptive weight fusion algorithm. The original measurement data of the sensor after discrete Kalman filtration are treated as a new fusion data source, which substitute the traditional method that obtains sensor measurement data directly as fusion data source. The fusion output results have faster convergence speed, better data smoothness, and higher fusion accuracy than improved before. The improved algorithm can avoid the interference of disturbance data and mutation data, provide a new method for time-series data fusion in the same space, and lay a foundation for the next research of soil data.

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 there are no conflicts of interest regarding the publication of this article.

Acknowledgments

This research was supported by Shaanxi Science and Technology Department Project (16JK1100) and Shaanxi Provincial Science and Technology Department Social Development Science and Technology Project (2016SF-418).

References

- [1] J. An, K. Wei, and L. Wang, "Research on precise irrigation control technology based on Internet of Things," *Journal of Northwest A&F University (Natural Science Edition)*, vol. 41, no. 12, pp. 220–221, 2013.
- [2] Y. Qin, H. Zhang, and S. Wang, *Kalman Filtering and Integrated Navigation Principles*, Xi'an: Northwestern Polytechnical University Press, Xi'an, China, 2nd edition, 2012.
- [3] D. Peng, "The basic principle and application of Kalman filter," *Software Guide*, vol. 11, p. 33, 2009.
- [4] L. Shen and C. Ma, "Soil conductivity measurement method based on data fusion," *Journal of Changchun University of Technology (Natural Science Edition)*, vol. 4, pp. 152–153, 2012.
- [5] X. Chen, L. Xia, and L. Bu, "Application of adaptive weighted fusion algorithm in image fire detection system," *Ship Electronic Engineering*, vol. 3, p. 53, 2011.
- [6] Y. Li and L. Zhang, "Multi-sensor adaptive weighted fusion algorithm and its application research," *Automation and Instrumentation*, vol. 2, pp. 10–12, 2008.
- [7] S. Wang, Na Jing, and Y. Xing, "Adaptive optimal parameter estimation and control of servo mechanisms: theory and experiment," *IEEE Transactions on Industrial Electronics*, 2020.
- [8] S. Wang and J. Na, "Parameter estimation and adaptive control for servo mechanisms with friction compensation," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 11, pp. 6816–6825, 2020.
- [9] S. Wang, L. Tao, Q. Chen, J. Na, and X. Ren, "USDE-based sliding mode control for servo mechanisms with unknown system dynamics," *IEEE/ASME Transactions on Mechatronics*, vol. 25, no. 2, pp. 1056–1066, 2020.
- [10] Q. Chen, X. Yu, M. Sun, C. Wu, and Z. Fu, "Adaptive repetitive learning control of PMSM servo systems with bounded nonparametric uncertainties: theory and experiments," *IEEE Transactions on Industrial Electronics*, 2020.
- [11] Q. Chen, H. Shi, and M. Sun, "Echo state network based backstepping adaptive iterative learning control for strict-feedback systems: an error-tracking approach," *IEEE Transactions on Cybernetics*, vol. 50, no. 7, 2020.
- [12] S. Wang, J. Na, X. Ren, H. Yu, and J. Yu, "Unknown input observer-based robust adaptive funnel motion control for nonlinear servomechanisms," *International Journal of Robust and Nonlinear Control*, vol. 28, no. 18, pp. 6163–6179, 2018.
- [13] Q. Guo, Y. Zhang, and B. G. Celler, "Neural adaptive backstepping control of a robotic manipulator with prescribed performance constraint," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 30, no. 2, pp. 3572–3583, 2019.
- [14] X. Zheng and P. Ren, "Application of wireless sensor network based on ZigBee in soil moisture monitoring," *Technology and Innovation*, vol. 7, pp. 8–9, 2017.
- [15] X. Hu and J. Zhao, "Design of soil moisture detection system based on ZigBee GPRS," *Modern Electronic Technology*, vol. 37, no. 6, pp. 59–61, 2014.
- [16] X. Li, Y. Zhang, and Z. Wei, "Application of Kalman filter in wireless clock synchronization technology," *Modern Electronic Technology*, vol. 43, no. 15, pp. 7–15, 2020.
- [17] Q. Fan, "UAV altitude estimation algorithm based on Kalman filter," *Electronic Design Engineering*, vol. 26, no. 21, pp. 135–138, 2018.
- [18] H. Luo and G. Li, "Research progress of soil moisture content detection," *Research on Agricultural Mechanization*, vol. 36, no. 5, pp. 244–247, 2014.
- [19] S. Shang, Y. Wang, A. Hong, and W. Wang, "Establishment of calibration equation of soil moisture content by near infrared spectroscopy," *Spectrum Laboratory*, vol. 28, no. 4, pp. 1603–1607, 2011.
- [20] L. Zhang, X. Yin, and Y. Chen, "Anti interference technology for data acquisition of Bathymetric Survey," *Marine Technology*, vol. 1, pp. 38–41, 2004.
- [21] R. Ruan, "Discussion on digital filtering technology," *Discussion on Digital Filtering Technology*, vol. 4, pp. 3–5, 1998.
- [22] Y. Shao, *Analysis of Indoor Noise Based on Virtual Instrument*, North University of Technology, Beijing, China, 2013.
- [23] M.-c. He, Z.-g. Tao, and B. Zhang, "Application of remote monitoring technology in landslides in the Luoshan mining area," *Mining Science and Technology (China)*, vol. 19, no. 5, pp. 609–614, 2009.
- [24] S. Shao and K. Zhang, "RISE-adaptive neural control for robotic manipulators with unknown disturbances," *IEEE Access*, vol. 8, no. 1, pp. 97729–97736, 2020.
- [25] F. Qin and W. Lifang, "Multiscale remote sensing image fusion algorithm based on variational segmentation," *Acta Electronica Sinica*, vol. 48, no. 6, pp. 1084–1090, 2020.
- [26] S. Shao, K. Wang, J. Li, and J. Wang, "Adaptive predefined performance neural control for robotic manipulators with unknown dead zone," *Mathematical Problems in Engineering*, vol. 2020, Article ID 6490167, , 2020.
- [27] Y. Gu, Z. Zhang, and Yi Shen, "Data acquisition and distributed remote control of wireless sensor nodes," *Radio Engineering*, vol. 50, no. 8, pp. 661–665, 2020.

- [28] P. Angrove, M. O'grady, and J. Hayes, "A mobile gateway for remote interaction with wireless sensor," *Networks in IEEE Sensors Journal*, vol. 12, pp. 3309-3310, 2011.
- [29] H. Kim and S.-W. Han, "An efficient sensor deployment scheme for large-scale wireless sensor networks," *IEEE Communications Letters*, vol. 19, no. 1, pp. 90-101, 2015.
- [30] M. Kalz, J. Garca-Zuba, and M. Fikar, "A flexible and configurable architecture for automatic control remote laboratories," *IEEE Transactions on Learning Technologies*, vol. 8, no. 3, pp. 299-310, 2015.
- [31] G. Wang, J. Yang, and Y. Deng, "Discussion on the accuracy of soil moisture automatic monitoring," *Hydrology*, vol. 33, no. 5, pp. 7-38, 2013.
- [32] X. Shi and G. Wang, "Research progress of soil moisture content measurement methods," *Rural Water Conservancy and Hydropower in China*, vol. 10, pp. 84-86, 2003.
- [33] B. Chen, J. Zhang, and C. Zhao, "Modern sensing technology is used to observe soil moisture," *Agricultural System Science and Comprehensive Research*, vol. 4, pp. 315-318, 1995.
- [34] Y. Zhao, "Design of airport environment multi parameter monitoring system based on ZigBee technology," *Electronic Design Engineering*, vol. 28, no. 15, pp. 61-69, 2020.
- [35] J. Xu, "Design of medical monitoring system based on ZigBee Technology," *Wireless Internet Technology*, vol. 17, no. 2, pp. 13-14, 2020.
- [36] X. Wang, "Design of wireless medical monitoring system based on ZigBee," *Journal of Changchun University*, vol. 29, no. 8, pp. 14-18, 2019.
- [37] H. Sun, "Design of temperature and humidity monitoring system for high speed EMU based on ZigBee," *Electronic Design Engineering*, vol. 25, no. 11, pp. 142-148, 2017.
- [38] G. Wang, Y. Li, and B. Yang, "Research on temperature and humidity monitoring system based on ZigBee," *Electronic Design Engineering*, vol. 21, no. 1, pp. 63-66, 2013.