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Research Article

Control Optimization of Stochastic Systems Based on Adaptive Correction CKF Algorithm

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Standard cubature Kalman filter (CKF) algorithm has some disadvantages in stochastic system control, such as low control accuracy and poor robustness. This paper proposes a stochastic system control method based on adaptive correction CKF algorithm. Firstly, a nonlinear time-varying discrete stochastic system model with stochastic disturbances is constructed. The control model is established by using the CKF algorithm, the covariance matrix of standard CKF is optimized by square root filter, the adaptive correction of error covariance matrix is realized by adding memory factor to the filter, and the disturbance factors in nonlinear time-varying discrete stochastic systems are eliminated by multistep feedback predictive control strategy, so as to improve the robustness of the algorithm. Simulation results show that the state estimation accuracy of the proposed adaptive cubature Kalman filter algorithm is better than that of the standard cubature Kalman filter algorithm, and the proposed adaptive correction CKF algorithm has good control accuracy and robustness in the UAV control test.

1. Introduction

Due to the influence of the external environment or uncertain factors, there is some stochastic noise in the control system [1, 2]. This kind of system with stochastic parameters is called stochastic system [3, 4]. Stochastic systems are perturbed by stochastic factors, so conventional control methods cannot accurately express the control process of the system [5, 6]. Therefore, it is significant to study methods to improve the control accuracy of stochastic systems.

At present, the control methods of stochastic systems can be divided into two categories: linear control method [7] and nonlinear control method [8]. The linear control method generally converts the input and output of the system into a superposition system and makes it conform to the linear distribution law [9]. Reference [10] proposes a decentralized control model for stochastic systems based on linear quadratic Gaussian model to deal with the uncertainty of financial markets. The linear stable feedback control of stochastic systems is carried out by using the antistable rate function, and the optimality of disturbance parameters is analyzed [11]. A control strategy based on coupled asymptotic structure is proposed for stochastic systems with multiplicative white noise disturbances [12]. A dynamic control mechanism of secondary load is proposed for stochastic systems with active demand response, which realizes real-time control of power equipment [13]. A linear matrix inequality (LMI) control method is proposed by combining the stochastic two-dimensional delay control model with the Lyapunov function [14]. A linear stochastic system control method based on improved Kalman filtering algorithm is proposed in [15]. The stochastic disturbances are optimized by recursive estimation of constrained states. A linear output control method for discrete stochastic systems is proposed [16]. The second-order unobservable stochastic sequence is used to describe the state of the system, and the optimal output control is realized. The nonstationary disturbance signal is modeled as a dynamic parameter with a small rate of change, and the discrete recursive least-squares algorithm is used for linear control of stochastic systems [17]. A linear control

strategy for stochastic systems with time delays is proposed by using the clustering decay estimation method of neural networks [18]. According to the characteristics of dynamically constrained stochastic systems, an adaptive linear control model is established by a non-Bayesian clustering algorithm [19].

Nonlinear control methods generally use a differential geometry principle or feedback linearization principle to transform the system linearly, so as to achieve the purpose of control [20]. A stochastic dynamical system control method based on optimal feedback control is proposed in reference [21]. The global control is realized by real-time feedback through nonlinear local state control. A Bayesian-based generalized control method for nonlinear discrete systems is proposed in [22]. According to the characteristics of state tracking stochastic systems, an observer-based control method is proposed in [23]. The equivalent input disturbance estimator is used to realize the antijamming. According to the characteristics of stochastic systems with state delay, an integrated sliding mode control strategy is proposed in [24]. According to the characteristics of stochastic systems in supply chain, a two-stage nonlinear mixed-integer programming control model is proposed in [25]. According to the characteristics of network malicious attack detection stochastic system, a linear control method of dynamic evolution stochastic handoff is proposed in [26]. Stochastic systems are transformed into multiobjective optimal design problems, and nonlinear control is performed by solving Hamiltonian trajectory systems [27]. State correlation coefficient decomposition and unknown input filtering are used to estimate system parameters, and robust two-stage Kalman filtering is used to construct a multistep estimator, robust simultaneous state, and fault estimator to realize the nonlinear control of stochastic systems [28]. An auxiliary virtual controller is designed by using the general approximator of neural network, and the nonlinear control of stochastic systems is realized by constraining the parameters of stochastic systems by coupling effect [29].

The linear control method has the advantages of high stability and high efficiency in the application of multivariable optimal control, but it requires high accuracy of data and is not suitable for complex stochastic systems. Although the nonlinear control method transforms the system linearly through the principle of calculus geometry or feedback linearization, it still has the problem of low control accuracy for large-scale complex stochastic nonlinear discrete systems. Therefore, aiming at this problem, this paper proposes a stochastic system control method based on adaptive correction CKF algorithm. The control model is established by using the volume Kalman filter algorithm. The control accuracy is improved by the optimization of covariance matrix, adaptive correction of memory factor, multistep feedback predictive control, and other strategies.

1.1. Nonlinear Time-Varying Discrete Stochastic Systems. The stochastic control system has the characteristics of uncertainty [30], such as the autonomous control system of unmanned aerial vehicle (UAV) [31], which is affected by unstable wind [32], electromagnetic interference [33], noise signal [34], and so on in the process of operation, resulting in its control system with nonlinear, discrete, time-varying, stochastic, and other characteristics [35]. A stochastic system can be represented in the form of Equations (1) and (2) [36].

$$x_{k+1} = f(x_k, r_k) + G_k s_k + \sigma_k, \tag{1}$$

$$y_{k+1} = g(x_{k+1}) + \eta_{k+1}. \tag{2}$$

y_{k+1} is a nonlinear time-varying discrete stochastic system y_{k+1} dimension state vector, y_{k+1} is a system $\sigma_k \sim N(0, P_w)$ dimension measurement vector, $\sigma_k \sim N(0, P_w)$ is an input value of the system, $\sigma_k \sim N(0, P_w)$ is a stochastic noise of the system, s_k is a noise observed by the system, s_k is an external interference factor to the system, and G_k is a distribution matrix of external interference.

In order to better perform the system state estimation, linearization processing is performed on $g(x_{k+1})$ in Equation (2), as shown in

$$B_{k+1} = \frac{\partial g(x_{k+1})}{\partial x_{k+1}}. \tag{3}$$

Substituting Equation (3) into Equation (2), the linearization processing result of Equation (2) is obtained.

$$y_{k+1} = B_{k+1} x_{k+1} + \eta_{k+1}. \tag{4}$$

Since there are external interference factors in the above-mentioned system, the disturbance observation matrix of the nonlinear time-varying discrete stochastic system is calculated for the unknown influence factors, as shown in

$$E_{k+1} = \left[(B_{k+1} G_{k+1})^T B_{k+1} G_{k+1} \right]^{-1} (B_{k+1} G_{k+1})^T. \tag{5}$$

Substituting Equation (4)–(5) into Equation (1), a nonlinear time-varying discrete stochastic system is obtained, as shown in

$$\begin{cases} \hat{x}_{k+1/k} = \bar{f}(\hat{x}_k, r_k) + \bar{G}_k y_{k+1}, \\ \hat{x}_{k+1} = \hat{x}_{k+1/k} + K_{k+1}(y_{k+1} - \hat{y}_{k+1/k}), \end{cases} \tag{6}$$

where K_{k+1} is the gain value at $k+1$ time.

1.2. Control Model of Stochastic Systems Based on CKF. For the nonlinear time-varying discrete stochastic system constructed above, a cubature Kalman filter (CKF) [37–39] algorithm is used to estimate the state of the system. Firstly, the cubature points of the system are calculated, as shown in

$$X_{i,k-1/k-1} = \sqrt{Q_{k-1/k-1}}\,\varepsilon_i + \hat{x}_{k-1/k-1}. \tag{7}$$

After the cubature point is propagated, it can be converted into the form of

$$\begin{cases} Z_{i,k/k-1} = m(X_{i,k/k-1}), \\ \hat{z}_{i,k/k-1} = \dfrac{1}{2n}\sum_{i=1}^{2n} Z_{i,k/k-1}. \end{cases} \tag{8}$$

The propagated filter gain matrix is obtained, as shown in

$$K_{k+1} = Q_{xz,k/k-1} Q_{zz,k/k-1}^{-1}. \tag{9}$$

Then, the perturbation observation matrix of the nonlinear time-varying discrete stochastic system is updated.

$$\begin{cases} \hat{x}_{k/k} = \hat{x}_{k/k-1} + K(z_k - \hat{x}_{k/k-1}), \\ Q_{k/k} = Q_{k/k-1} - K_k Q_{zz,k/k-1} K_k^T. \end{cases} \tag{10}$$

1.3. Algorithm Simulation Test. The experiment 1 environment is constructed to simulate and test the abovementioned CKF-based stochastic system control model. The input value of the system is $r_k = 2$, the stochastic noise σ_k is the stochastic value at (0, 1), the total step size is 650, and the output value y is the estimate of the state of the system. Then, the comparison results between the actual value of the system and the estimated value of the state are shown in Figure 1 and Table 1.

According to the results of Figure 1 and Table 1, the error is statistically analyzed, and the result is shown in Figure 2 and Table 2.

From the above results, the standard error of the cubature Kalman Filter algorithm for nonlinear time-varying discrete stochastic systems is about 0.2, and the influence of external disturbances on it needs to be improved.

2. Cubature Kalman Filter Algorithm with Adaptive Correction

2.1. State Estimation of Stochastic Disturbances. The nonlinear time-varying discrete stochastic systems studied in this paper have stochastic interference factors. The standard CKF algorithm eliminates errors easily in the process of operation, which leads to the lack of error correction ability of error covariance matrix. In this paper, the covariance matrix of standard CKF is optimized by square root filter.

Set the state values of nonlinear time-varying discrete stochastic systems is $x_{k/k}$, the state estimate is $\hat{x}_{k/k}$. The covariance matrix is $Q_{k-1/k-1}$.

$$J_{k-1/k-1} = \text{Cholesky}(Q_{k-1/k-1}). \tag{11}$$

$J_{k-1/k-1}$ is the decomposed square root. According to Equation (11) and Equation (7), the cubature point calculation equation of the system is shown in

$$X_{i,k-1/k-1} = J_{k-1/k-1}\varepsilon_i + \hat{x}_{k-1/k-1}. \tag{12}$$

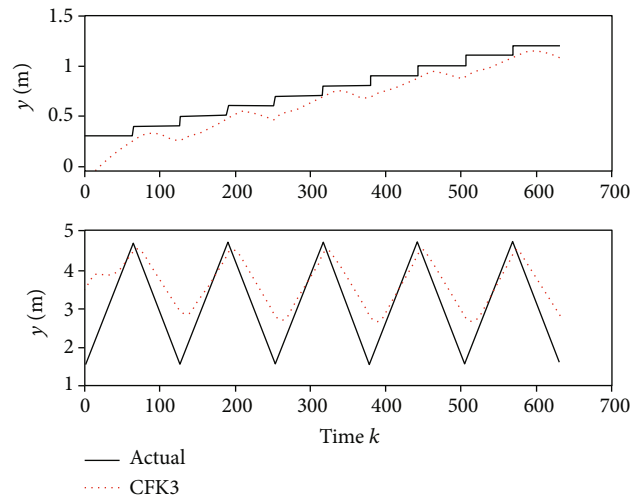

Figure 1: Comparison of state estimates based on CKF.

Table 1: Comparison of actual and state estimates.

Time (s)	Estimated value (m)	
	Actual	CKF
1	1.5891	2.7976
50	4.0028	3.5643
100	2.9186	3.6121
150	2.6976	2.7937
200	4.2194	4.4373
250	1.7211	2.8640
300	3.9325	3.7625
350	3.0035	3.7202
400	2.6422	2.8742
450	4.3065	4.4705
500	1.8009	2.9697
550	3.8061	3.7212
600	3.1030	3.7877
650	1.6087	2.7903

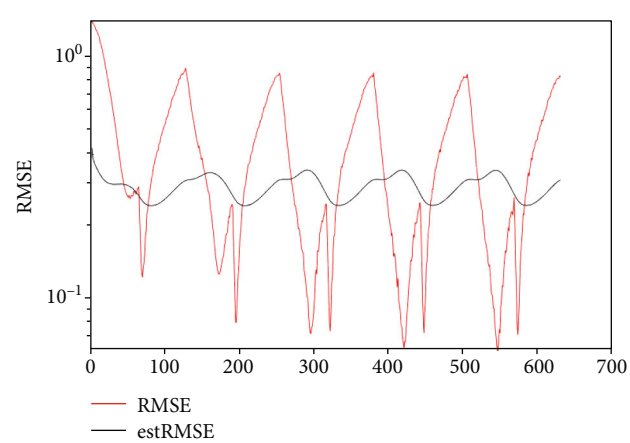

Figure 2: Results of error comparison analysis based on CKF.

Table 2: Statistics of error comparison.

Time (s)	RMSE	estRMSE
1	1.4814	0.4266
50	0.2615	0.3123
100	0.5401	0.2632
150	0.3772	0.3267
200	0.1766	0.2483
250	0.8398	0.3103
300	0.1108	0.3307
350	0.5101	0.2606
400	0.2061	0.3203
450	0.1329	0.2519
500	0.8315	0.3078
550	0.0792	0.3370
600	0.4848	0.2577
650	0.8426	0.3133

The predicted value at the next time is obtained by the propagation of the cubature point, as shown in

$$\hat{x}_{k/k-1} = \sum_{i=1}^{2mn} Z_i \times f\left(X_{i,k-1/k-1}\right). \tag{13}$$

Calculating the square root of the error covariance matrix from the predicted values is given by [14]:

$$R^*_{k/k-1} = U \sum_{i=1}^{2mn} X^*_{i,k/k-1} - \hat{x}_{k/k-1}, \tag{14}$$

$$L_{k/k-1} = qr\left[R^*_{k/k-1}\sqrt{M_k}\right]. \tag{15}$$

M_k is the covariance of the stochastic noise σ_k of the system, and $qr[]$ is the matrix decomposition operation.

2.2. Adaptive Correction of System Noise. Considering the mismatch between error covariance matrix and system observation noise as the number of iterations increases, this paper adaptively corrects the error covariance matrix based on the optimization of state estimation.

First, the error covariance is used to determine whether the system state is different, and the real-time error information of the system can be represented by the innovation ρ_k of the covariance matrix, as shown in

$$\rho_k = x_k - Q\bar{x}_{k+1/k}. \tag{16}$$

Then, the prior estimation covariance matrix ρ^i_k of the system is

$$\rho^i_k = G\left[\bar{\delta}\cdot\bar{\delta}^T\right], \tag{17}$$

$$\bar{\delta} = \bar{x}^i_{k/k-1} - x_k. \tag{18}$$

When $\rho_k\rho^T_k > Q^i_k Q^T + R^i_k$, the system state is deviated, a memory factor α is added to change the memory length of the CKF so as to ensure the error convergence of the filter, and the calculation method is as follows:

$$\alpha = \frac{\hat{x}^{iT}_{k-1}\cdot\hat{x}^i_{k-1} - d\left[QQ^T + R^i_k\right]}{d\left[AQ^i_{k-1}A^TQ^T\right]}, \tag{19}$$

where d is the trace of the systematic error covariance matrix.

The information vectors of the node i and the corresponding matrices are then calculated, as shown in

$$\begin{cases} c_i = Q^T_i R^{i-1}_k x^i_k, \\ C_i = Q^T_i R^{i-1}_k Q_i. \end{cases} \tag{20}$$

Fusion of the nearest points is performed for each of the nodes described above, as shown in

$$\begin{cases} z_i = \sum\limits_{i\in N_i\cup i} c_i, \\ Z_i = \sum\limits_{i\in N_i\cup i} C_i. \end{cases} \tag{21}$$

A priori estimate is updated for the result of the node fusion, as shown in

$$\hat{x}^i_{k+1/k+1} = \bar{x}^i_{k+1/k} + \frac{c_i - C_i\bar{x}^i_{k+1/k}}{Q^{i-1}_k + C_i} + \beta\sum_{i\in N_i}\bar{x}^i_{k+1/k}. \tag{22}$$

The calculation equation of β is

$$\beta = \frac{\eta_k}{1 + \left\|I - \left(Q^{i-1}_k + C_i\right)^{-1}C_i\right\|}. \tag{23}$$

Finally, the error covariance matrix is adaptively corrected by the updated prior estimates.

2.3. Predictive Control with Figure Feedback. Due to the existence of external disturbance factor s_k in nonlinear time-varying discrete stochastic systems, a multistep feedback predictive control strategy is proposed to ensure the convergence and stability of the system.

The input constraints and the output probability constraints of a nonlinear time-varying discrete stochastic system are determined, as shown in

$$\begin{cases} x^A < x_{i/k} < x^B, \\ \Pr\left\{y_{k+i} \notin \left[y^A, y^B\right]\right\} < p. \end{cases} \tag{24}$$

A and B are, respectively, the upper and lower limits of the parameters of nonlinear time-varying discrete stochastic systems.

The solution is then obtained using probability theory, as shown in

$$\theta_p = \mathrm{Co}\left\{d^i, i = 1, 2\right\}. \tag{25}$$

In order to make the nonlinear time-varying discrete stochastic system not exceed the polyhedron region in control, the robust optimization is carried out according to the requirement of confidence level.

$$\theta = \mathrm{Co}\left\{d_m^j, j = 1, 2, \cdots, k\right\}. \tag{26}$$

Then, the observer and feedback control rate satisfying the condition of Equation (27) are applied to the nonlinear time-varying discrete stochastic system at k time.

$$K - G\left(A_k^T K A_k\right) \succ 0, \quad K \succ 0. \tag{27}$$

And calculate the performance metric function matrix $\tilde{X}_k$:

$$\tilde{X}_k = \left(\Gamma_{k/k-1}^i \tilde{X}^{-1} \Gamma_k\right)^{-1}. \tag{28}$$

The invariant set max det $(\tilde{X}_{i,k}^{-1})$ is obtained according to the performance index function matrix. If the invariant set is not in the polyhedron region, the invariant set is eliminated, and the observation parameter matrix is obtained again.

3. Performance Simulation of Improved CKF Algorithm

In order to verify the algorithm proposed in this paper, the performance simulation of the adaptive correction volume Kalman filter algorithm is carried out in the environment of experiment 1. The input value of the system is set at $r_k = 2$, the stochastic noise σ_k is a stochastic value at (0, 1), the total step size is 650, and the output value y is the system state estimation value. The results of the stochastic disturbance state estimation optimization (CKF1) are shown in Figure 3, the results of the system noise adaptive correction (CKF2) are shown in Figure 4, the results of the multistep feedback predictive control (CKF3) are shown in Figure 5, and the comparison results are shown in Table 3.

The error statistics of CKF1 after optimization of stochastic disturbance state estimation are shown in Figure 6, the error statistics of CKF2 after adaptive system noise correction are shown in Figure 7, the error statistics of CKF3 after multistep feedback predictive control are shown in Figure 8, and the error comparison results are shown in Table 4.

It can be seen from the results in Figures 3–8 and Table 4 that the average error of state estimation is 0.404 after the optimization of state estimation of random disturbance; 0.3344 after the adaptive correction of system noise; and 0.2654 after the multistep feedback predictive control. Therefore, the accuracy of the proposed adaptive volume Kalman filter algorithm is improved compared with that of the standard volume Kalman filter algorithm according to the feedback of real-time correction of the error covariance matrix from the real-time observation value of external interference factors.

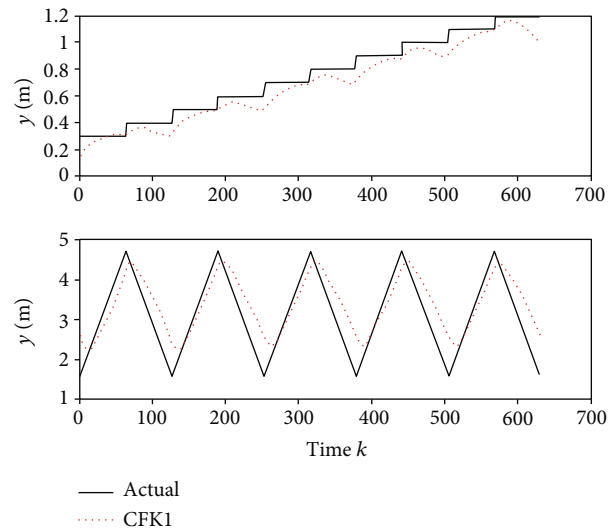

Figure 3: State estimation results after optimization of stochastic disturbance state estimation.

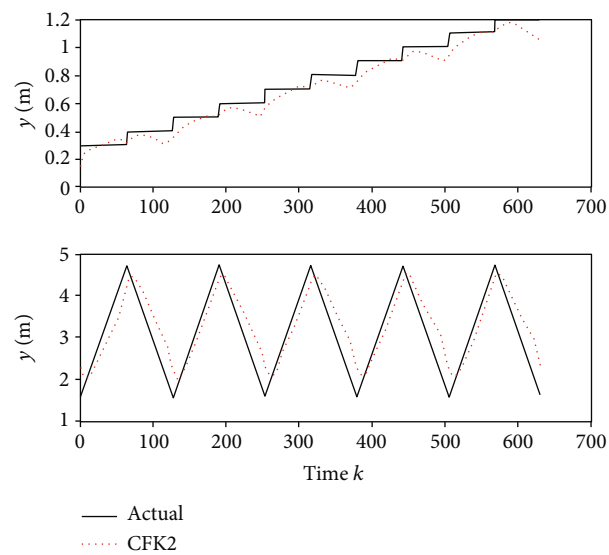

Figure 4: State estimation results after adaptive system noise correction.

4. Simulation Test of Unmanned Aerial Vehicle Control System

In order to verify the control effect of the improved algorithm in the actual stochastic system, in this paper, the control system of unmanned aerial vehicle (UAV) is simulated and tested. Because of the influence of unknown disturbance, the control system of UAV is nonlinear, discrete, time-

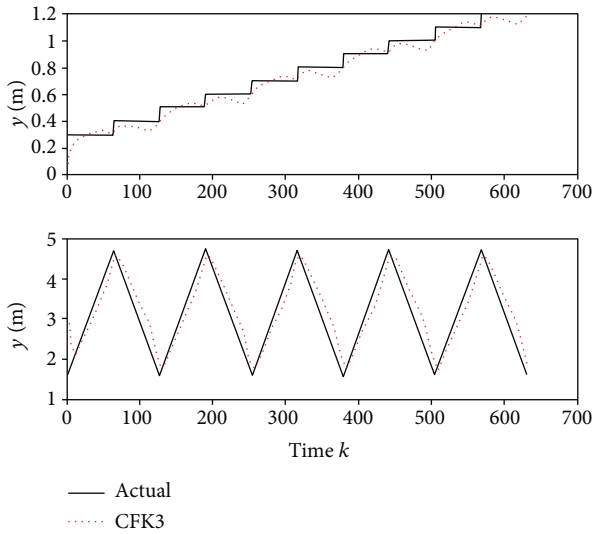

Figure 5: State estimation results after multistep feedback predictive control.

Table 3: Comparison of actual and state estimates.

Time (s)	Estimated value (m)			
	Actual	CKF1	CKF2	CKF3
1	1.5891	2.3986	1.7611	3.9831
50	4.0028	3.3611	3.2017	4.1643
100	2.9186	3.5768	3.5268	3.7309
150	2.6976	2.6998	2.6061	3.3523
200	4.2194	4.4186	4.4011	4.4737
250	1.7211	2.8431	2.8121	2.9358
300	3.9325	3.7408	3.7185	3.8267
350	3.0035	3.7161	3.7141	3.7251
400	2.6422	2.8770	2.8600	2.9138
450	4.3065	4.4713	4.4747	4.4750
500	1.8009	2.9677	2.9708	2.9727
550	3.8061	3.7192	3.7232	3.7228
600	3.1030	3.7878	3.7890	3.7858
650	1.6087	2.7859	2.7889	2.7954

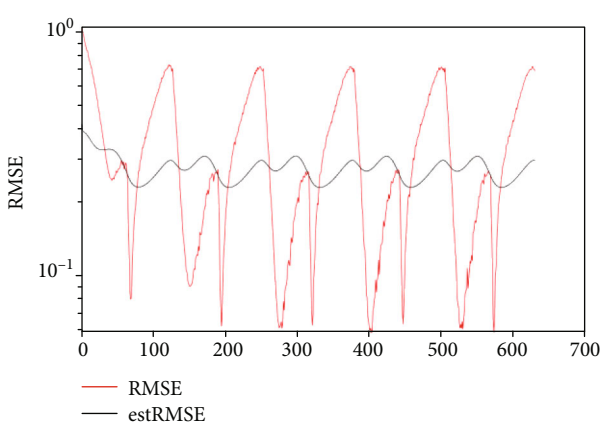

Figure 6: State estimation results after optimization of stochastic disturbance state estimation.

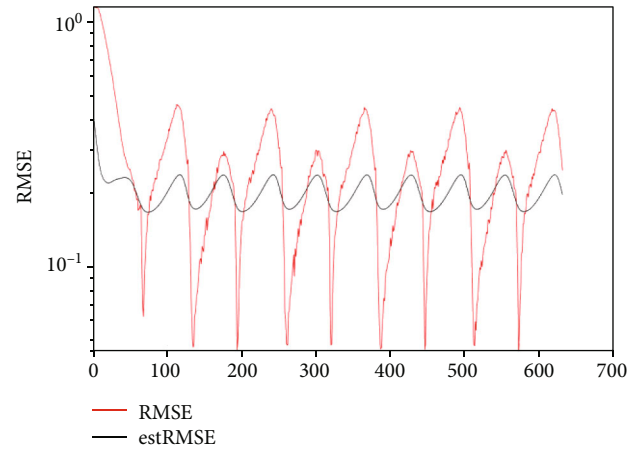

Figure 7: State estimation results after adaptive system noise correction.

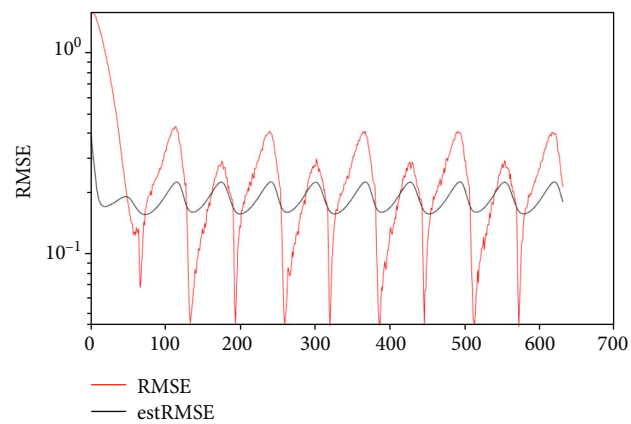

Figure 8: State estimation results after multi-step feedback predictive control.

Table 4: Error comparison results of improved algorithms.

Time (s)	RMSE		
	CKF1	CKF2	CKF3
1	0.8949	1.3408	1.1951
50	0.4418	0.3354	0.1829
100	0.4727	0.3370	0.2069
150	0.2284	0.3228	0.3042
200	0.1624	0.1701	0.1746
250	0.8017	0.4356	0.2242
300	0.1343	0.1117	0.1212
350	0.4913	0.2035	0.1005
400	0.2013	0.2175	0.2187
450	0.1259	0.1299	0.1340
500	0.8189	0.3337	0.2297
550	0.0801	0.0757	0.0914
600	0.4830	1.3408	1.1951
650	0.8362	0.3354	0.1829

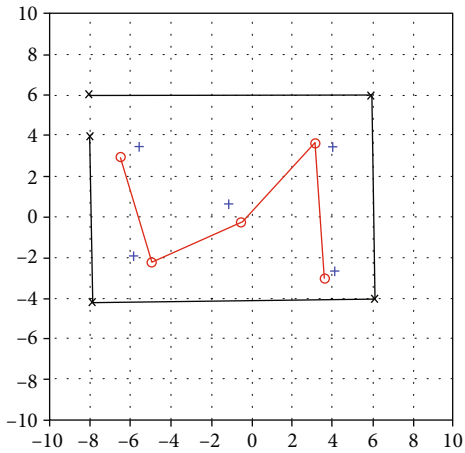

Figure 9: Environment diagram of experiment 1.

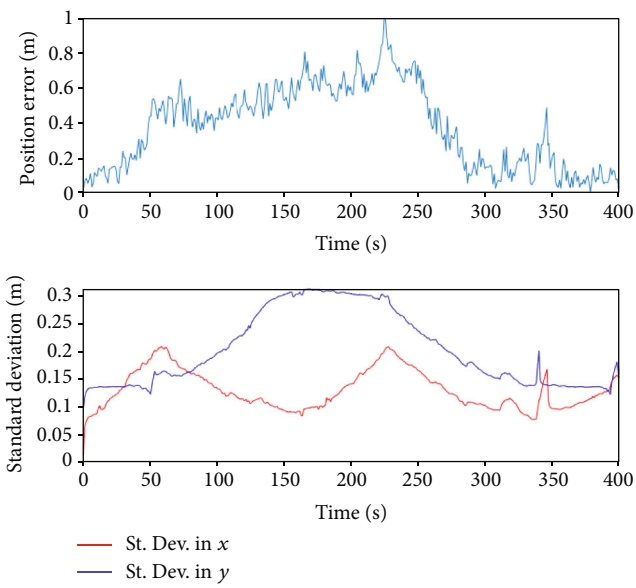

Figure 10: Improved algorithm control results.

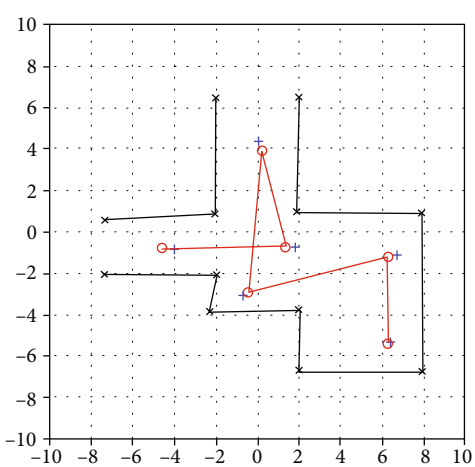

Figure 11: Experiment 2 environment schematics.

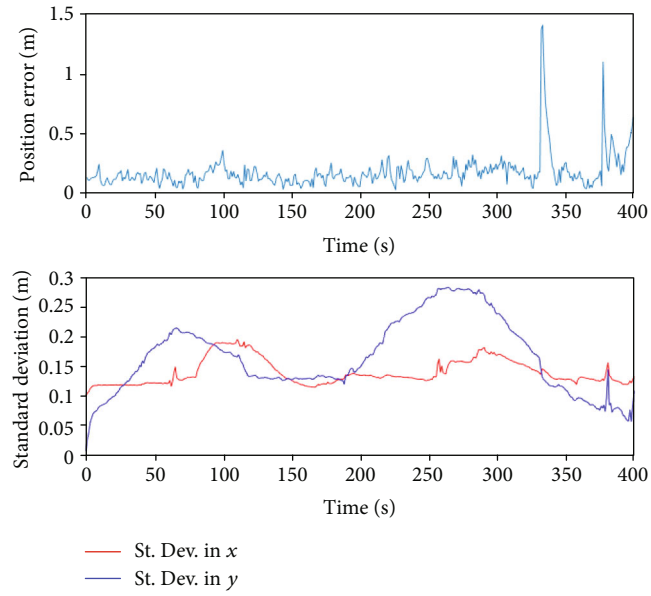

Figure 12: Improved algorithm control results for Experiment 2 environment.

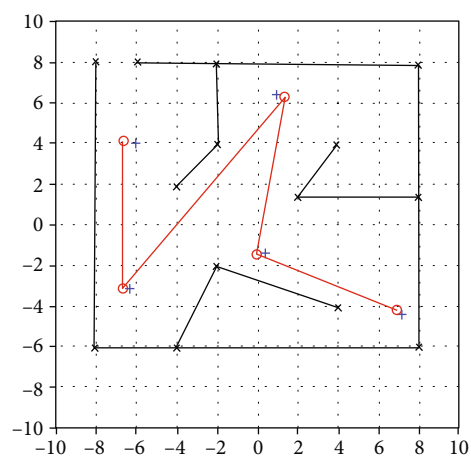

Figure 13: Experiment 3 environment schematics.

varying, stochastic, and so on. The control system of UAV belongs to a very typical stochastic system.

$$\bar{X}(t) = A_X X(t) + B_X u_\theta(t) + M_X \lambda_X(t). \tag{29}$$

A is the flight speed of the UAV, u_θ is the angular speed of the UAV, B is the size parameters of the UAV, t is the flight time, and λ is the unknown interference of the environment to the UAV.

In this simulation experiment, three different indoor obstacle sites were set up to test the control effect of the improved algorithm, and five path points (such as "+" in the figure) and standard running trajectory (such as "O" in the figure) were set up. The environment of experiment 1 is shown in Figure 9.

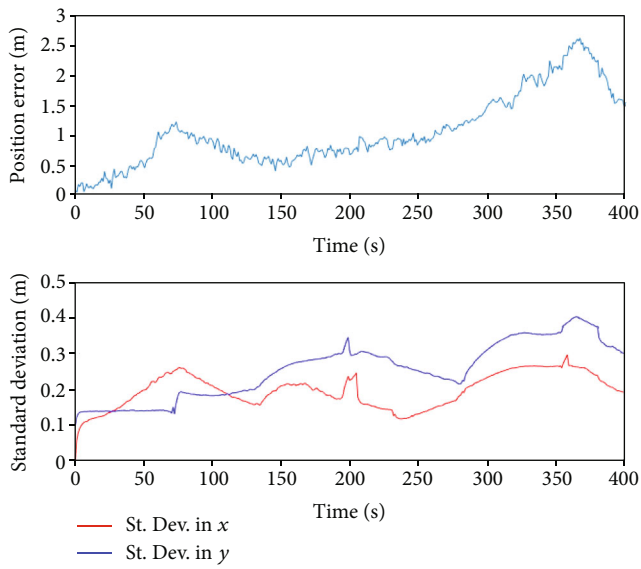

Figure 14: Improved algorithm control results for experiment 3 environment.

Table 5: Improved algorithm control error statistics for experiment 3 environment.

Time (s)	Position error (m)		
	Test 1	Test 2	Test 3
1	0.0737	0.0427	0.0480
50	0.5071	0.2345	0.1676
100	0.7955	0.4957	0.0160
150	1.0664	0.3200	0.1988
200	1.6095	0.2282	0.0264
250	1.6441	0.5999	0.0771
300	0.7354	0.5275	0.1190
350	0.0210	0.2350	0.1481
400	0.8197	0.1762	0.0709

A stochastic value of 1 m wheelbase, 0.5 m rotor length, 1.5 m/s maximum flight speed, 0.5 rad/s maximum angular speed, and (0.02, 0.1) unknown interference is set as the input value of Equation (29), and the control error result of the improved algorithm is shown in Figure 10.

Dev.in x and Dev.in y represent the accuracy error of the UAV in the x-axis and y-axis, respectively, the same below.

The environment for experiment 2 is shown in Figure 11.

The control error results of the improved algorithm in the environment of experiment 2 are shown in Figure 12.

The environment for experiment 3 is shown in Figure 13.

The control error results of the improved algorithm in the environment of experiment 3 are shown in Figure 14.

The control error statistics of the improved algorithm in three simulation tests are shown in Table 5.

From the above simulation results, it can be seen that the average error of position estimation is 0.81 M in the environment of experiment 1, 0.32 m in the environment of experiment 2, and 0.10 m in the environment of experiment 3. So it can be seen that, with the continuous change of environmental complexity, the improved algorithm proposed in this paper still maintains a certain degree of control accuracy and stability and has a certain degree of robustness for external interference.

5. Summary

Stochastic system control is widely used in aerospace, intelligent robot, intelligent manufacturing, and other fields. It can effectively carry out fault diagnosis, fault-tolerant control, real-time system detection, and so on. Aiming at the shortcomings of standard CKF algorithm in stochastic system control, such as low control accuracy and poor robustness, a stochastic system control method based on the adaptive correction CKF algorithm is proposed in this paper. Experimental results show that the proposed algorithm has better control accuracy and robustness in stochastic system control.

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 is no conflict of interests regarding the publication of this paper.

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References

[1] L. I. Allerhand, E. Gershon, and U. Shaked, "Robust state-feedback control of stochastic state-multiplicative discrete-time linear switched systems with dwell time," *International Journal of Robust and Nonlinear Control*, vol. 26, no. 2, pp. 187–200, 2016.

[2] J. A. Paulson and A. Mesbah, "An efficient method for stochastic optimal control with joint chance constraints for nonlinear systems," *International Journal of Robust and Nonlinear Control*, vol. 29, no. 15, pp. 5017–5037, 2017.

[3] B. Niu, D. Wang, H. Li, X. Xie, N. D. Alotaibi, and F. E. Alsaadi, "A novel neural-network-based adaptive control scheme for output-constrained stochastic switched nonlinear systems," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 49, no. 2, pp. 418–432, 2019.

[4] A. A. Malikopoulos, "A duality framework for stochastic optimal control of complex systems," *IEEE Transactions on Automatic Control*, vol. 61, no. 10, pp. 2756–2765, 2016.

[5] X. Liu, Y. Ge, and Y. Li, "Stackelberg games for model-free continuous-time stochastic systems based on adaptive dynamic programming," *Applied Mathematics and Computation*, vol. 363, article 124568, 2019.

[6] C. Hua, Y. Li, L. Zhang, and X. Guan, "Adaptive state feedback control for time-delay stochastic nonlinear systems based on dynamic gain method," *International Journal of Control*, vol. 92, no. 12, pp. 2806–2819, 2018.

[7] S. H. Lee, M. J. Park, O. M. Kwon, and R. Sakthivel, "Master-slave synchronization for nonlinear systems via reliable control with Gaussian stochastic process," *Applied Mathematics and Computation*, vol. 290, pp. 439–459, 2016.

[8] A. S. Poznyak, "Sliding mode control in stochastic continuos-time systems: μ-zone *MS*-Convergence," *IEEE Transactions on Automatic Control*, vol. 62, no. 2, pp. 863–868, 2017.

[9] F. J. Hu, "Simulation and analysis of airbag parameter variation under different gas flows," *Cluster Computing*, vol. 22, no. S6, pp. 13235–13245, 2019.

[10] R. Singh, P. R. Kumar, and L. Xie, "Decentralized control via dynamic stochastic prices: the independent system operator problem," *IEEE Transactions on Automatic Control*, vol. 63, no. 10, pp. 3206–3220, 2018.

[11] E. S. Palamarchuk, "On the optimal control problem for a linear stochastic system with an unstable state matrix unbounded at infinity," *Automation and Remote Control*, vol. 80, no. 2, pp. 250–261, 2019.

[12] V. Dragan and H. Mukaidani, "Optimal control for a singularly perturbed linear stochastic system with multiplicative white noise perturbations and Markovian jumping," *Optimal Control Applications and Methods*, vol. 38, no. 2, pp. 205–228, 2017.

[13] G. Benysek, J. Bojarski, R. Smolenski, M. Jarnut, and S. Werminski, "Application of stochastic decentralized active demand response (DADR) system for load frequency control," *IEEE Transactions on Smart Grid*, vol. 9, no. 2, pp. 1055–1062, 2018.

[14] R. Sakthivel, T. Saravanakumar, B. Kaviarasan, and S. Marshal Anthoni, "Dissipativity based repetitive control for switched stochastic dynamical systems," *Applied Mathematics and Computation*, vol. 291, pp. 340–353, 2016.

[15] J. Prakash, D. Zamar, B. Gopaluni, and E. Kwok, "An efficient model based control algorithm for the determination of an optimal control policy for a constrained stochastic linear system," *IFAC-PapersOnLine*, vol. 51, no. 18, pp. 590–595, 2018.

[16] A. V. Bosov, "Discrete stochastic system linear output control with respect to a quadratic criterion," *Journal of Computer and Systems Sciences International*, vol. 55, no. 3, pp. 349–364, 2016.

[17] S. Dong, L. Yu, W. A. Zhang, and B. Chen, "Recursive identification for Wiener non-linear systems with non-stationary disturbances," *IET Control Theory & Applications*, vol. 13, no. 16, pp. 2648–2657, 2019.

[18] L. Pan, J. Cao, U. A. al-Juboori, and M. Abdel-Aty, "Cluster synchronization of stochastic neural networks with delay via pinning impulsive control," *Neurocomputing*, vol. 366, pp. 109–117, 2019.

[19] A. Abdollahi and G. Chowdhary, "Adaptive-optimal control under time-varying stochastic uncertainty using past learning," *International Journal of Adaptive Control and Signal Processing*, vol. 33, no. 12, pp. 1803–1824, 2019.

[20] F. Hu, "Sliding mode control of discrete chaotic system based on multimodal function series coupling," *Mathematical Problems in Engineering*, vol. 2017, Article ID 8423413, 11 pages, 2017.

[21] T. Rajpurohit and W. M. Haddad, "Partial-state stabilization and optimal feedback control for stochastic dynamical systems," *Journal of Dynamic Systems, Measurement, and Control*, vol. 139, no. 9, article 091001, 2017.

[22] I. K. Dassios and K. J. Szajowski, "Bayesian optimal control for a non-autonomous stochastic discrete time system," *Applied Mathematics and Computation*, vol. 274, pp. 556–564, 2016.

[23] R. Sakthivel, L. Susana Ramya, and P. Selvaraj, "Observer-based state tracking control of uncertain stochastic systems via repetitive controller," *International Journal of Systems Science*, vol. 48, no. 11, pp. 2272–2281, 2017.

[24] K. Khandani, V. J. Majd, and M. Tahmasebi, "Integral sliding mode control for robust stabilisation of uncertain stochastic time-delay systems driven by fractional Brownian motion," *International Journal of Systems Science*, vol. 48, no. 4, pp. 828–837, 2016.

[25] P. S. A. Cunha, F. M. P. Raupp, and F. Oliveira, "A two-stage stochastic programming model for periodic replenishment control system under demand uncertainty," *Computers and Industrial Engineering*, vol. 107, pp. 313–326, 2017.

[26] A. Cetinkaya, H. Ishii, and T. Hayakawa, "Analysis of stochastic switched systems with application to networked control under jamming attacks," *IEEE Transactions on Automatic Control*, vol. 64, no. 5, pp. 2013–2028, 2019.

[27] J. Umenberger and T. B. Schon, "Nonlinear input design as optimal control of a Hamiltonian system," *IEEE Control Systems Letters*, vol. 4, no. 1, pp. 85–90, 2020.

[28] T. Bessaoudi, F. B. Hmida, and C. S. Hsieh, "Robust state and fault estimation for non-linear stochastic systems with unknown disturbances: a multi-step delayed solution," *IET Control Theory and Applications*, vol. 13, no. 16, pp. 2556–2570, 2019.

[29] J. Wang, Z. Liu, Y. Zhang, and C. L. P. Chen, "Neural adaptive event-triggered control for nonlinear uncertain stochastic systems with unknown hysteresis," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 30, no. 11, pp. 3300–3312, 2019.

[30] Q. Lan and S. Li, "Global output-feedback stabilization for a class of stochastic nonlinear systems via sampled-data control," *International Journal of Robust and Nonlinear Control*, vol. 27, no. 17, pp. 3643–3658, 2017.

[31] A. Mesbah, "Stochastic model predictive control with active uncertainty learning: a survey on dual control," *Annual Reviews in Control*, vol. 45, pp. 107–117, 2018.

[32] A. V. Panteleev and K. A. Rybakov, "Optimal continuous stochastic control systems with incomplete feedback: approximate synthesis," *Automation and Remote Control*, vol. 79, no. 1, pp. 103–116, 2018.

[33] S. Karthikeyan, M. Sathya, and K. Balachandran, "Controllability of semilinear stochastic delay systems with distributed delays in control," *Mathematics of Control, Signals, and Systems*, vol. 29, no. 4, p. 17, 2017.

[34] T. Rajpurohit and W. M. Haddad, "Nonlinear-nonquadratic optimal and inverse optimal control for stochastic dynamical systems," *International Journal of Robust and Nonlinear Control*, vol. 27, no. 18, pp. 4723–4751, 2017.

[35] H. Xu, H. Yuan, K. Duan, W. Xie, and Y. Wang, "Adaptive high-degree cubature Kalman filter in the presence of unknown measurement noise covariance matrix," *The Journal of Engineering*, vol. 2019, no. 19, pp. 5697–5701, 2019.

[36] P. C. P. M. Pardal, R. V. Garcia, H. K. Kuga, and W. R. Silva, "An investigation on cubature Kalman filter performance for orbit determination application," *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, vol. 41, no. 10, article 43, 2019.

[37] H. Huang, R. Shi, J. Zhou et al., "Attitude determination method integrating square-root cubature Kalman filter with expectation-maximization for inertial navigation system applied to underwater glider," *Review of Scientific Instruments*, vol. 90, no. 9, article 095001, 2019.

[38] A. Ramezani, B. Safarinejadian, and J. Zarei, "Fractional order chaotic cryptography in colored noise environment by using fractional order interpolatory cubature Kalman filter," *Transactions of the Institute of Measurement and Control*, vol. 41, no. 11, pp. 3206–3222, 2019.

[39] F. Hu and G. Wu, "Distributed error correction of EKF algorithm in multi-sensor fusion localization model," *IEEE Access*, vol. 8, pp. 93211–93218, 2020.