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Research Article

Positioning of Tower Crane Trolley Based on D-S Evidence Theory and Kalman Filter

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Due to the complex structure of the tower crane and the signal noise, it is difficult to estimate and predict the real position signal, which may lead to inaccurate positioning of the tower crane trolley. A tower crane positioning algorithm based on D-S evidence theory and unscented Kalman filter (DS-UKF) is established and developed. First, the nonlinear dynamic model, state equation, and detection equation of the tower crane are constructed based on the complex structure of the tower crane. Second, the arm angle is estimated, and the distance between the trolley and the root of the arm is positioned. Finally, in order to calculate the weight of a single sensor, the D-S evidence theory is used to process the measurement information of the sensor and the estimated value of the filter. The Kalman filter, which has good signal tracking and estimation ability, is used to predict and estimate the position of the trolley. The accurate positioning of the tower crane trolley is realized through the organic fusion of information. The simulation results show the effectiveness of the DS-UKF positioning algorithm.

1. Introduction

The tower crane is a kind of commonly used heavy machinery, which was originated in Western Europe. The working space is large, the main work is the installation of building components and the transmission of materials in the building, and the working mechanism has lifting, luffing, turning, and so on. Due to inertia, external environment such as wind speed, construction site, and other factors, the load may appear to swing vibration phenomenon in the lifting process, and the boom, trolley, and load cannot reach the target accurately, which will seriously affect the productivity. So, it is very important to complete the accurate positioning of the tower structure, which can ensure the efficiency and safety of the tower operation.

However, it is difficult to achieve accurate positioning of the tower cranes. When the tower crane is started, braked, or coupled, the structure of the tower crane will bear strong impact and vibration, and there is a complex nonlinear system in the tower crane structure. In addition, multivariable and multicoupling is a major difficulty in tower crane positioning, such as positioning control and swing angle control, affecting each other. The change of rope length, load weight, and speed during the operation of the tower crane will affect the accuracy of the tower crane positioning.

There are many current localization techniques. The multisensor information fusion tracking is a hot research topic, which can process information from multiple sensors or multiple sources based on certain information fusion algorithms to produce more reliable estimates and judgments.

There are also many methods of multisensor fusion, such as the Kalman filtering, D-S evidence theory, neural networks, and many other methods. The multisensor fusion has been used in some applications. A combined positioning system based on multi-information fusion is designed in the literature [1] to solve the positioning error problem of multiaxis emergency rescue vehicles when driving in complex environments. However, the D-S evidence theory still has shortcomings in the application field, which is widely used in fault diagnosis [2], target recognition [3], and other fields. Although heavy machinery accounts for a large proportion in the industrial field, the D-S evidence theory has not been widely applied to it.

The positioning system of the tower crane trolley is nonlinear, and the ordinary Kalman filtering algorithm does not apply to the nonlinear system. It is necessary to use the extended Kalman filter (EKF) or the unscented Kalman filter (UKF). Both algorithms can be used for nonlinear systems. The extended Kalman filter fusion algorithm can be used for the positioning of tower cranes [4, 5], and in literature [4], the authors proposed a multiparameter sequential extended Kalman filter algorithm (MS-EKF) based on radial acceleration and radial velocity. The extended Kalman filter (EKF) is applied to the measurement equations of radial acceleration and radial velocity using state filter values. A scheme consisting of a robust fast model predictive controller (FTMPC) and a design extended Kalman filter (EKF) target observer is proposed in the literature [5] to solve the motion target grasping problem. The unscented Kalman filter could also be applied to the positioning of tower cranes, and the application of the federal UKF multisource information fusion algorithm to the tower crane positioning system is proposed in the literature [6]. However, the EKF algorithm retains only the first-order term of the Taylor series expansion, which loses too much data and requires complex Jacobian matrix computation, which significantly reduces the positioning accuracy for the tower crane nonlinear system with strong white noise. The UKF algorithm has higher accuracy and stability for nonlinear systems, but it has some disadvantages, such as the parameter selection problem needs to be solved, and the filtering effect is influenced by the initial value of the filter, as in the EKF algorithm.

When multiple independent sensors are used to track a dynamic target, the measurement value and noise characteristics of each sensor are different, which can easily lead to large deviation. An algorithm is essential to fuse the measurements of multiple sensors to obtain a better state vector of the system. Due to the changeful external environmental factors and the different nature of different sensors, some unmeasurable variables are brought, which reduce the measurement accuracy of sensors and makes it difficult to estimate the state of tower cranes. In view of how to deal with the inevitable error problem in actual engineering measurement, some scholars have proposed good solutions for different research objects. For example, in literature [7], a differential pressure fitting method of an asymmetric differential pressure cylinder is proposed for pneumatic system leakage, which overcomes the limitation of detection efficiency caused by the asynchronous temperature recovery of two chambers in the asymmetric differential pressure method and effectively improves the impact of environmental pressure fluctuations or electromagnetic noise interference of sensors on detection. In literature [8], for Takagi–Sugeno fuzzy system models of discrete-time interval type-2 with measurable and unmeasurable premise variables, a functional observer is proposed to estimate this new state vector for unknown input or state estimation. Two examples are given to illustrate the effectiveness of this method. However, because of the complicated structure and nonlinear system of the tower crane, it is difficult to directly fit the sensor error and construct an observer model, so the previous methods do not adapt well to the positioning problem of the tower crane. The application of the D-S evidence theory to data fusion does not require prior knowledge, which is conducive to solving the problems of large data error and data uncertainty. Therefore, the D-S evidence theory and the UKF algorithm are simultaneously applied to the tower crane positioning system in this study, and the measurement information in the sensors is synthesized by the D-S evidence theory to get more accurate measurement information. The information is filtered by the UKF algorithm, which is better to solve the nonlinearity problem existing in the tower crane system, and also get a better estimation to realize the precise positioning of the trolley.

2. Nonlinear Positioning System

The motions of a tower crane can be divided into rotation of the tower arm, movement of the tower crane trolley, and lifting of the load. Considering the difficulty of installing the angular velocity and angular velocity measurement equipment, a nonlinear system is created by combining the arm and the car [9]. The system model is shown in Figure 1.

In Figure 1, a represents the arm angle, $v1$ represents the rotation speed, s represents the distance between the car and the arm root, and $v2$ represents the moving speed of the car.

A plane is created through the root of the boom and perpendicular to the boom before the boom moves. $l1(k)$ and $l2(k)$ represented the distance between the tip of the boom and the plane and the distance between the tower crane trolley and the plane, respectively. Then, the equations of state and measurement equations of the system were established based on the established model and the relationship between each variable.

Therefore, the equation of the state of the system is

$$\begin{bmatrix} a(k) \\ v_1(k) \\ s(k) \\ v_2(k) \end{bmatrix} = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} a(k-1) \\ v_1(k-1) \\ s(k-1) \\ v_2(k-1) \end{bmatrix} + \begin{bmatrix} \omega_1(k-1) \\ \omega_2(k-1) \\ \omega_3(k-1) \\ \omega_4(k-1) \end{bmatrix}, \tag{1}$$

where T is the sampling period, $\omega(k)$ means the white noise with mean 0 and positive definite covariance $G(k)$, and $\omega(k)$ means the state noise matrix.

From the geometric relationship in Figure 1, the following formula is obtained:

$$\begin{cases} l_1(k-1) = L\cos a(k-1) \\ l_2(k-1) = s(k-1)\cos a(k-1) \end{cases}. \tag{2}$$

The resulting nonlinear measurement equation for the system is

$$\begin{bmatrix} l_1(k-1) \\ l_2(k-1) \end{bmatrix} = \begin{bmatrix} L\cos a(k-1) \\ s(k-1)\cos a(k-1) \end{bmatrix} + \begin{bmatrix} v_1 \\ v_2 \end{bmatrix}, \tag{3}$$

where L is the length of the arm and $V(k)$ is the white noise with zero mean and positive definite covariance of $O(k)$.

So far, the state equation and the measurement equation had been established, and the measurement equation is in a nonlinear form.

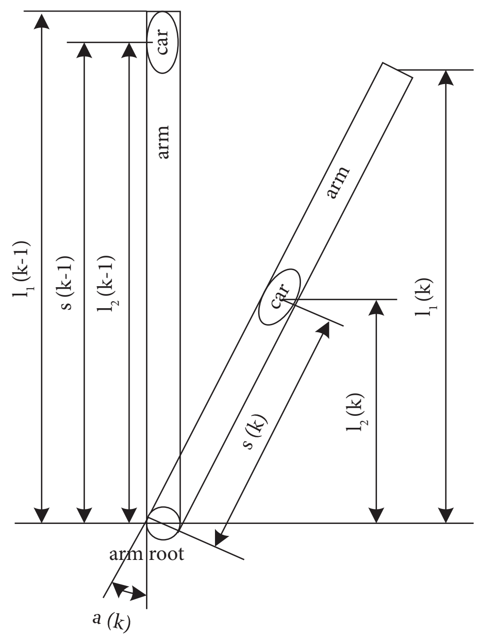

Figure 1: Model of trolley and arm.

3. Unscented Kalman Filtering

The UKF algorithm is a method based on the UT transform, a new method for computing the statistical properties of random variables in nonlinear transformations.

The basic principle of the UT transform is shown as follows. Assume a nonlinear system $y = g(x)$, where x is an n-dimensional state vector, and it is known that its mean is $\overline{x}$ and variance is $P(x)$, and the statistical properties of y can be obtained by constructing $2n + 1$ Sigma points through the UT transform and constructing the corresponding weights at the same time.

The formula for constructing the Sigma point set is as follows:

$$\begin{cases} x_0 = \overline{x}, i = 0; \\ x_i = \overline{x} + [\sqrt{(n+\lambda)}\, p]_i, i = 1, \ldots, n; \\ x_i = \overline{x} - [\sqrt{(n+\lambda) p}\,]_i, i = n+1, \ldots, 2n; \end{cases} \quad (4)$$

where λ repents the scale factor.

$$\lambda = \alpha^2 (n + k) - n. \quad (5)$$

The set of sampled points x_i can approximate the Gaussian distribution of the state x. Then, the transformation of the nonlinear function $f(x_i)$ is performed on x_i to obtain the function value $\{y_i\}$. The mean and variance of the output quantity were obtained by weighting $\{y_i\}$, and the algorithm is as follows:

$$\begin{cases} p_y \approx \sum_{i=0}^{2n} W_i^{(c)} (y_i - y)(y_i - y)^T \\ y \approx \sum_{i=0}^{2n} W_i^{(m)} y_i \end{cases}. \quad (6)$$

Among them,

$$\begin{cases} W_0^{(m)} = \dfrac{\lambda}{n+\lambda} \\ W_0^{(c)} = \dfrac{\lambda}{n+\lambda} + 1 - \alpha^2 + \beta \end{cases}. \quad (7)$$

The weights for finding the expectation and the weights for finding the variance were the same for the remaining $2n$ Sigma points [10].

$$W_i^{(m)} = W_i^{(c)} = \frac{1}{2(n+\lambda)}, i = 1, \ldots, 2n. \quad (8)$$

The UT transform is characterized by approximating the probability density distribution of a nonlinear function instead of approximating a nonlinear function. Even if the system model is complex, it did not increase the difficulty of algorithm implementation [11, 12]. The statistical accuracy of the obtained nonlinear functions can reach the third order; moreover, it does not require the computation of Jacobi matrices and can handle non-derivable nonlinear.

4. D-S Evidence Theory

D-S evidence theory, also known as the Dempster–Shafer evidence theory, is used to deal with uncertain or inaccurate information. The set of propositions of interest to the D-S evidence theory is represented by an "identification framework Θ" that defines a set function as follows:

$$m: 2^\Theta \longrightarrow [0, 1]. \quad (9)$$

Then, $m(A)$ is the basic probability assignment (BPA) function of A. If A belongs to the identification framework Θ, $m(A)$ is called the basic credibility of A.

For any set of propositions, the D-S evidence theory also proposed the notion of a confidence function that

$$Bel(A) = \sum_{B \subset A} m(B). \quad (10)$$

The credibility function of A is the sum of the credibilities of each subset of the evidence that contains the elements of A.

The synthetic law for the two confidence levels is

$$\begin{aligned} m(A) = m_1(A) \oplus m_2(A) &= \frac{\sum_{A_i \cap B_j = A} m_1(A_i) m_2(B_j)}{k} k \\ &= 1 - \sum_{A_i \cap B_j = \phi} m_1(A_i) m_2(B_j). \end{aligned} \quad (11)$$

k denotes the conflict coefficient between the evidence, which reflects the degree of conflict between the evidence [13, 14]. If $k \neq 0$, the combination between two sets of evidence can be viewed as an orthogonal sum; if $k = 0$, it indicates the contradiction between the evidence.

5. D-S Evidence Theory and UKF Filter Fusion

The concept of entropy in information theory is used to measure the importance of each evidence in the synthesis process. If the conflict between certain evidence and other evidence is greater, then the information entropy is greater and the weight is smaller; on the contrary, the conflict is smaller, and then the weight of that evidence is greater. Thus, the weight vector is determined [15, 16].

At any moment in the tower crane trolley motion process, the data of the trolley and the tower crane arm motion collected by each sensor are the evidence.

First, a recognition framework is constructed to determine the basic trolley position from the information conveyed by each sensor: the distance of the car from the arm root and the angle of the arm rotation. However, due to the error of the sensor itself and the influence of environmental factors, the trolley position cannot be precisely located. The current possible position estimate of the tower crane trolley is used to construct the identification framework, then Θ is the set of all possible positions of the tower crane trolley.

The BPA of the evidence is then reassigned.

$$\mathrm{Set}P_{m_i}(x_{ti}) = \sum_{x_{tj}\in\Theta} \frac{\left|x_{ti}\cap xt_j\right|}{\left|x_{tj}\right|} m(x_{ti}). \tag{12}$$

x_{ti} and x_{tj} are the focal elements of the recognition framework, and $\mathrm{Set}Pm_i(x_{ti})$ represents the degree of support of the basic probability assignment for each subset. In this study, it represents the degree of support for the current moment position of the tower crane trolley.

Second, the conflict difference of the same focal element under different evidence is calculated.

$$\begin{aligned} Diff_{m_i}^{m_j}(x_t) &= \left|\mathrm{Set}P_{m_i}(x_t) - \mathrm{Set}P_{m_j}(x_t)\right|, \\ i'j &= 1,2,\ldots N, t = 1,2,\ldots n. \end{aligned} \tag{13}$$

The conflict difference is normalized as shown in the following equation:

$$\alpha_{xt} = \frac{\mathrm{Diff}_{m_i}^{m_j}(x_t)}{\sum_{t=1}^{n}\mathrm{Diff}_{m_i}^{m_j}(x_t)}, t = 1,\ldots,n, \tag{14}$$

satisfying $\sum_{t=1}^{n}\alpha_{x_t} = 1$.

The normalized value of the exponential entropy operation:

$$H_t = \sum_{t=1}^{n}\alpha_{x_t} e^{\left(1-\alpha_{x_t}\right)}. \tag{15}$$

The value of entropy and the weights can be considered reciprocal operations, so the weights can be expressed as

$$\beta_t = \frac{1}{H_t}, t = 1,\ldots,n. \tag{16}$$

Finally, the cosine theorem of a trigonometric function is introduced to fix the entropy value between [0, 1] and assign weights by using the curve property of the cosine function, and the obtained weights are smoother.

$$\omega_t = \cos\left(\beta_t \times \frac{\pi}{2}\right). \tag{17}$$

This determines the weight vector consisting of the weight coefficients of each evidence.

In this study, the D-S evidence theory and the UKF filtering algorithm are applied to the positioning of the tower crane trolley, and the structural framework of the fusion idea is shown as follows.

$x_1\cdots x_n$: Information on the distance between the trolley and the arm root.

$\hat{x}_1\cdots\hat{x}_n$: Distance information after filtering.

$\theta_1\cdots\theta_m$: Information about the corner of the tower crane arm.

$\hat{\theta}_1\cdots\hat{\theta}_m$: Corner information after filtering.

Y‘Z: The information sequence after D-S fusion of the measured information.

$\hat{Y}$‘$\hat{Z}$: Measurement information after the information sequence is filtered by the UKF algorithm.

Figure 2 shows that the evidence of the received information is the measured information received by the different sensors and the information that passes through the filter.

$$\begin{aligned} m_i &= \left[x_i, \hat{x}_i\right], i = 1,\ldots,n, \\ m_j &= \left[\theta_j, \hat{\theta}_j\right], j = 1,\ldots m. \end{aligned} \tag{18}$$

Then, the information received by the sensor about the distance of the trolley from the boom root, the rotation angle of the tower crane boom, and the filtered information after the subfilter is synthesized according to the D-S improvement algorithm, and then, the weight ratio of the information received by the sensor at different moments is

$$\begin{aligned} \omega_k &= \left[\omega_{1k}, \omega_{2k}, \ldots \omega_{nk}\right], \\ \omega_t &= \left[\omega_{1t}, \omega_{2t}, \ldots \omega_{mt}\right], \end{aligned} \tag{19}$$

where k and t denote moments, and i and j denote the number of sensors.

The new information sequence after fusion is

$$\begin{aligned} Y &= \sum_{i=1}^{n}\hat{x}_i \times \omega_k^T, \\ Z &= \sum_{i=1}^{m}\hat{x}_i \times \omega_t^T, \end{aligned} \tag{20}$$

where T denotes the transpose.

In summary, two different sensors are used in this study, namely, radar sensor and angle sensor. The distance of the tower crane trolley from the boom root and the boom angle obtained by the sensor are used as the measurement information (the distance between the trolley and the boom root and the boom angle can accurately locate the tower crane trolley). The filtered information obtained after the filter together become the evidence of the D-S algorithm. After the D-S algorithm is used to obtain the weight ratio of the information received by the sensor at different times, the

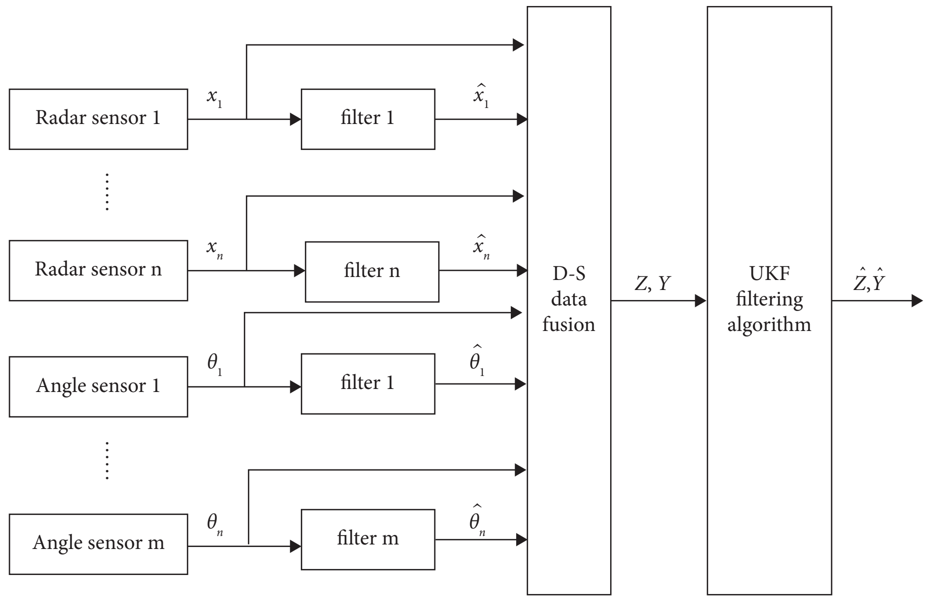

Figure 2: Fusion algorithm framework.

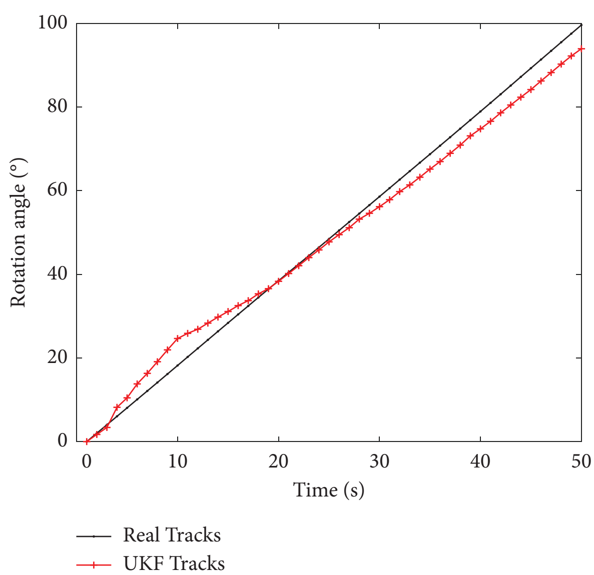

Figure 3: UKF positioning of a boom angle.

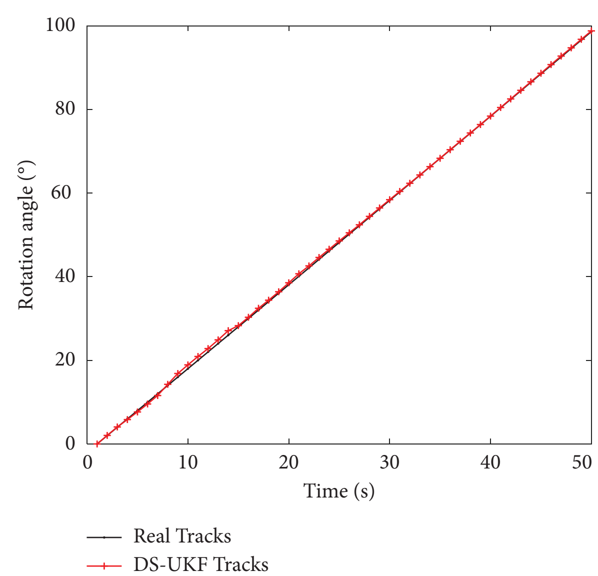

Figure 4: D-S and UKF fusion positioning of a boom angle.

true degree of the information conveyed by the sensor can be known from the weight ratio. The conflict evidence can be weakened through the integration of the D-S algorithm, thereby obtaining more accurate car positioning information. The information is filtered by the UKF algorithm through information fusion. Finally, an ideal filtering effect is obtained. The information is then filtered by the UKF algorithm through information fusion to obtain a more ideal filtering effect.

6. Simulation Results

To verify the effectiveness of the proposed algorithm, in this study, the simulations with the DS-UKF combined algorithm and UKF algorithm, respectively, are designed and completed for a tower crane trolley.

Suppose the initial values

$$
\begin{aligned}
&a(k-1) = 0^{o}{}'s(k-1) = 10m, v1(k-1) = \frac{3^{o}}{s} \quad . \\
&v_2(k-1) = \frac{1m}{s}, L = 100m
\end{aligned}
\tag{21}
$$

The UKF algorithm parameters are given as follows:

$$
\alpha = 0.9\grave{\beta} = 2\grave{\lambda} = 2\grave{k} = 3.4. \tag{22}
$$

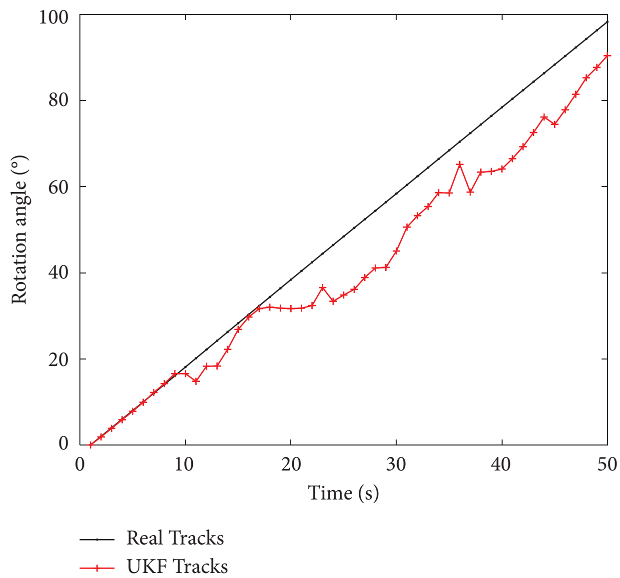

Figure 5: UKF positioning of the arm angle when noise increases.

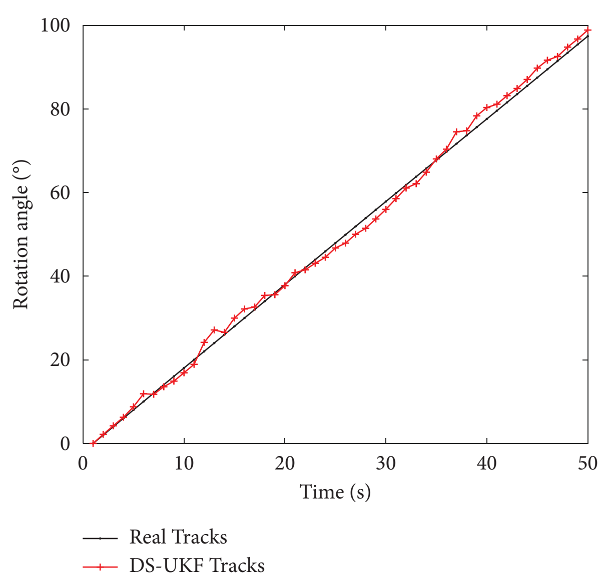

Figure 6: D-S and UKF fusion positioning of the arm angle when noise increases.

The simulation results are shown in Figures 3–10. Among them, Figures 3–6 show the effect of arm corner positioning, and Figures 7–10 show the simulation effect of trolley positioning at the distance from the arm root. Increasing the measurement noise (mean value of 0, positive definite covariance of 0.5, 0.25 white noise) means increasing the influence of measurement noise, weakening the system correction weights, and reducing the system transient response and steady-state values. The positioning of the tower crane trolley is performed again after increasing the measurement noise to twice the original one for comparing. Figures 5, 6, 9, and 10 show the simulation results when the measurement noise is considered and introduced.

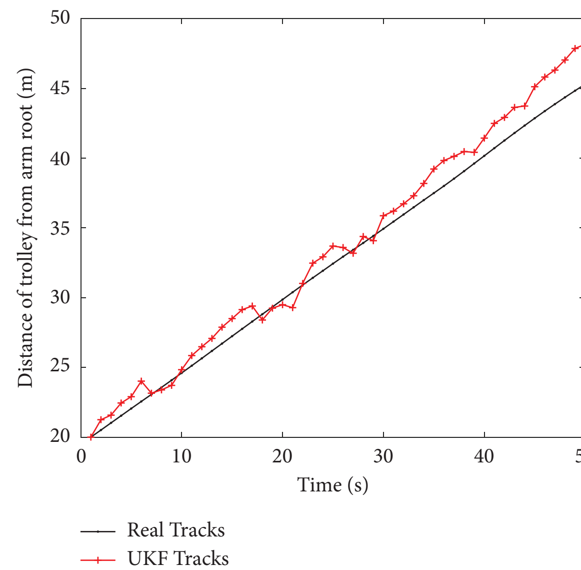

Figure 7: Distance between trolley and boom root UKF positioning.

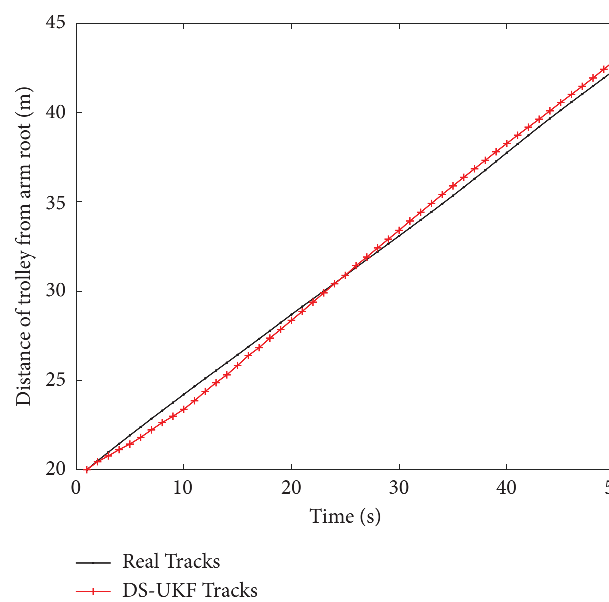

Figure 8: Distance between trolley and boom root DS-UKF fusion positioning.

According to the simulation results, it can be seen that when the UKF algorithm is used alone to localize the tower crane trolley, the effect is less satisfactory and has a tendency to diverge. When the UKF and D-S algorithms are used in combination, the localization effect is significantly improved, and there is no obvious divergence.

To verify the robustness of the algorithm, the simulation is carried out again after adding the disturbance. From Figures 5, 6, 9, and 10, when the noise interference is increased, the UKF algorithm alone is used to locate the tower crane, which has a more obvious divergence trend, and the positioning effect is worse. There is no obvious divergence

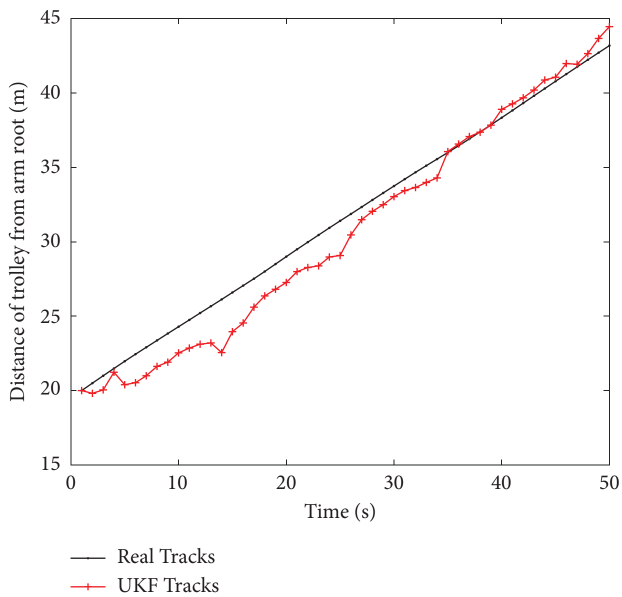

Figure 9: UKF positioning between trolley and boom root when noise increases.

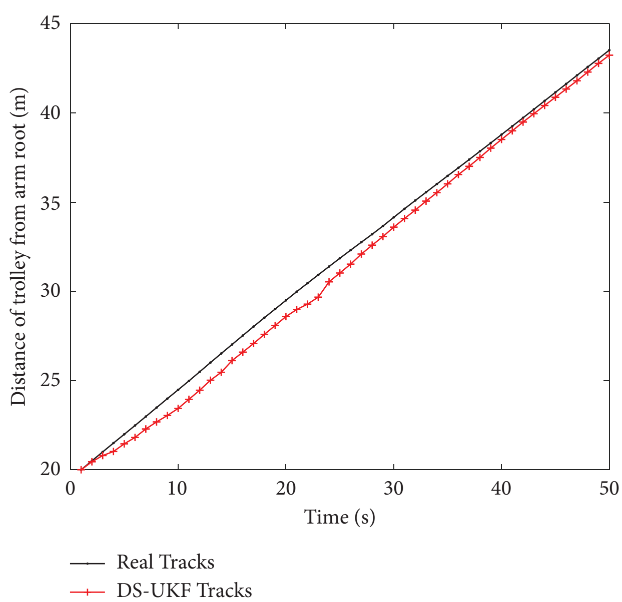

Figure 10: Distance between trolley and boom root DS-UKF fusion positioning when noise increases.

trend when the UKF and D-S algorithm are combined to locate the car. Although the positioning effect is also affected by noise, it is within the error range. Therefore, it can be seen that the proposed algorithm has good robustness.

7. Conclusion

In this study, the combination of the D-S evidence theory and UKF filtering algorithm is introduced to locate the tower crane trolley and reduces the impact of measurement errors on the system due to the sensor's own errors by processing the measurement data with the D-S evidence theory. The processed data are filtered by UKF, and the accuracy is greatly improved. The simulation results show that the precise positioning of the tower crane trolley is still achieved even in the case of increasing interference, and the algorithm has good anti-interference ability.

Data Availability

The digital data used to support the findings of this study have not been made available because the project signed a data confidentiality agreement.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

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References

[1] S. Xiaobo, Z. Dingxuan, and K. Zhifei, "High precision vehicle positioning technology based on multi-sensor information fusion [J/OL]," *China Mechanical Engineering*, vol. 33, no. 19, pp. 2381–2387, 2022.

[2] F. Ren, "Application of multi-sensor information fusion technology in hydraulic system fault diagnosis [J]," *Hydraulics pneumatics & seals*, vol. 39, no. 07, pp. 52–55, 2019.

[3] N. Zhao, *Research on Vehicle Recognition Algorithm Based on Evidence Theory [D]*, Xi'an University of technology, China, 2018.

[4] S. Jia, W. Sun, and G. Wang, "Maneuvering target tracking algorithm based on muti-paramter sequential extended kalman filter[J]," *Journal of Donghua University*, vol. 35, no. 03, pp. 207–214, 2018.

[5] Y. Dai, S. Yu, Y. Yan, and X. Yu, "An EKF-based fast tube MPC scheme for moving target tracking of a redundant underwater vehicle-manipulator system," *IEEE*, vol. 24, no. 6, pp. 2803–2814, 2019.

[6] Z. Chen, H. Wang, and J. Zhang, "Positioning system of tower crane based on federal UKF information fusion," *Journal of Information and Computational Science*, vol. 11, no. 17, pp. 6167–6174, 2014.

[7] Y. Li, M. Yuan, and M. Chadli, "Unknown input functional observer design for discrete time interval type-2 takagi-sugeno fuzzy systems[J]," *IEEE Transactions on Fuzzy Systems*, vol. 30, no. 11, pp. 4690–4701, 2022.

[8] Y. Shi, J. Chang, Y. Wang, and L. Yang, "Analysis on influence factors of differential pressure detection of gas leakage," *Journal of Sensors*, vol. 2022, no. 1, Article ID 9973299, 12 pages, 2022.

[9] Q. Shi, Y. Su, and A. Qiu, "Zhu Xinhua MEMS gyroscope device level vacuum packaging technology," *[J] Optical precision engineering*, vol. 17, no. 08, pp. 1987–1992, 2009.

[10] G. Liu and X. Wang, "Application of adaptive UKF algorithm in multi-target tracking and positioning system," *Journal of*

Physics: Conference Series, vol. 2146, no. 1, Article ID 012005, 2022.

[11] V. Lippiello, B. Siciliano, and L. Villani, "Adaptive extended Kalman filtering for visual motion estimation of 3D objects," *Control Engineering Practice*, vol. 15, no. 1, pp. 123–134, 2007.

[12] Z. Fu and Y. Han, "Centroid weighted Kalman filter for visual object tracking," *Measurement*, vol. 45, no. 4, pp. 650–655, 2012.

[13] Q. Liu, W. Wang, and X. Zhang, "Shang Jiale Information fusion method of command and control system based on improved DS evidence theory," *Fire and command and control*, vol. 47, no. 02, pp. 82–87, 2022.

[14] D. Liu, J. Zhang, J. Jin, Y. Dai, and L. Li, "A new approach of obstacle fusion detection for unmanned surface vehicle using Dempster-Shafer evidence theory," *Applied Ocean Research*, vol. 119, Article ID 103016, 2022.

[15] X.-J. Sun, Y. Gao, Zi-Li. Deng, C. Li, and J.-W. Wang, "Multi-model information fusion Kalman filtering and white noise deconvolution," *Information Fusion*, vol. 11, no. 2, pp. 163–173, 2010.

[16] J. Kang and Y. Gu, "Li Yibing Multisensor information fusion algorithm based on DS evidence theory," *Chinese Journal of inertial technology*, vol. 20, no. 06, pp. 670–673, 2012.