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Data Fusion Techniques for Enhanced UAV Near-Ground Distance Measurement Using Point and Surface Sensors

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Abstract: Accurate near-ground distance measurement is crucial for UAV navigation, particularly in complex environments. Traditional single-sensor systems face challenges in precision and real-time performance. This paper explores data fusion methods using laser point sensors and ultrasonic surface sensors to enhance measurement accuracy and stability. By comparing adaptive weighted fusion and Kalman filter algorithms, we identify the superior approach for combining point and surface sensor data. Experimental results demonstrate that the Kalman-based fusion algorithm significantly improves data accuracy, reduces mutation issues, and provides robust performance in agricultural UAV applications.

Keywords: Kalman filter; data fusion; laser ranging; ultrasonic ranging

1. Introduction

When the UAV collects the near-ground distance, it detects the distance from the target on one side [1] and moves forward to complete the predetermined task [2]. If the UAV 's near-ground ranging system is only a single type of sensor (such as a point sensor), the error of the concave and convex surface may be significantly increased, which will greatly affect the experimental results, and because the UAV is constantly moving during flight, the detection results before and after are very different, which will affect the precise positioning of the obstacle [3] [4]. The use of different types of multi-sensors for acquisition distance will effectively improve the real-time and accuracy of the system.

At present, the main types of sensors in ranging application technology are point ranging and surface ranging. The point ranging sensor has the advantages of high precision and low power consumption, but its scene coverage is limited and the dynamic target adaptability is poor. The characteristics of the surface ranging sensor are exactly complementary to it, and it has the advantages of strong adaptability to complex environment and multi-point measurement. In order to increase the stability and robustness after data fusion, this paper selects laser sensor and ultrasonic sensor as point sensor and surface sensor respectively to obtain experimental data.

The data fusion processing methods mainly include minimum variance estimation and maximum likelihood estimation and linear minimum variance estimation and Kalman filtering. The minimum variance estimation needs to know the conditional probability distribution density of the estimated value and the observed value, as well as their joint probability distribution density. The maximum likelihood estimation needs to know the conditional probability distribution density of the estimated value and the observed value [5][6]; the maximum posteriori estimation needs to know the observed value and the estimated conditional probability distribution density. The linear minimum variance estimation needs to know the first and second moments of the observed value and the estimated value.

The Kalman filtering algorithm and the adaptive weighted fusion estimation algorithm do not need to know any prior knowledge of the sensor measurement data, and only rely on the actual data collected by the sensor itself, the fusion estimation value with the smallest mean square error can be fused [7][8][9]. When the real value of the algorithm to be estimated is constant, the fusion result has high accuracy. When the real value to be measured is a very large amount. Based on the research of this problem, this paper compares the two data on the basis of Reference [10], and obtains a more reliable data fusion algorithm in our practice, so that it can be better applied to the online real-time processing of the real value to be measured.

2. Algorithm steps and comparison

2.1. Kalman filtering algorithm

After we collect data from two different ranging sensors, each data contains real data values and error values. The specific filtering and denoising processing steps are as follows:

Firstly, the process model is established, and then the system state at the previous moment is used to predict the state at the next moment:

$$X_{(k|k-1)} = AX_{(k-1|k-1)} + BU_{(k)} \quad (1)$$

Among them, $X_{(k|k-1)}$ it is the prediction of the current system state at the previous moment ; $X_{(k-1|k-1)}$ is the system state of the previous moment ; $U_{(k)}$ for the system control quantity at time k, since the system state does not change in the test, body of the work $U_{(k)} = 0$, A and B is the state transition matrix $A = I$, where I is the unit matrix.

The current update of the covariance matrix of the system is:

$$P_{(k|k-1)} = AP_{(k-1|k-1)}A^T + Q \quad (2)$$

where $P_{(k|k-1)}$ is the covariance matrix of the current moment relative to the previous moment; $P_{(k-1|k-1)}$ is the covariance matrix of the previous moment ; Q is the covariance matrix of the system process.

To predict the current state, the formula is as follows:

$$X_{(k|k)} = X_{(k|k-1)} + K_{g(k)}\left(Z_{(k)} - HX_{(k|k-1)}\right) \quad (3)$$

$$K_{g(k)} = \frac{P_{(k|k-1)}H^T}{HP_{(k|k-1)}H^T + R} \quad (4)$$

Among them, $Z_{(k)}$ is the signal measurement value at the moment; H is the measurement matrix and $H = I$; K_g is the Kalman gain ; R is the measurement noise covariance, which can be obtained by observation.

Update the covariance matrix, the formula is as follows:

$$P_{(k|k)} = \left(I - K_{g(k)}H\right)P_{(k|k-1)} \quad (5)$$

Therefore, the state prediction and covariance matrix of the current k moment can be obtained, and the two are substituted into the operation of the next moment to repeat the operation, so as to obtain the prediction result. The block diagram of its discrete linear system is shown in Figure 1:

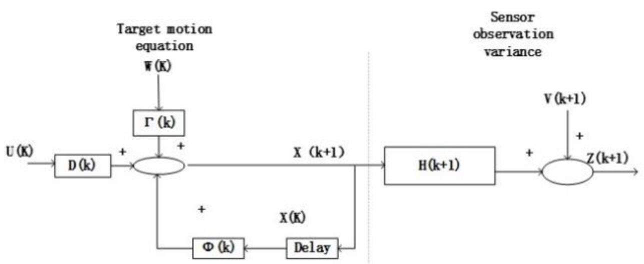

Fig.1.Block diagram of discrete linear system

2.2. Online adaptive weighted fusion estimation algorithm

The adaptive weighting algorithm is a commonly used data fusion algorithm. Its characteristic is that it does not need to obtain the prior knowledge of the sensor. The fusion calculation can be performed only by the data measured by the sensor, and the result of the minimum mean square error is obtained. The weighted algorithm fusion schematic is shown in Figure 2:

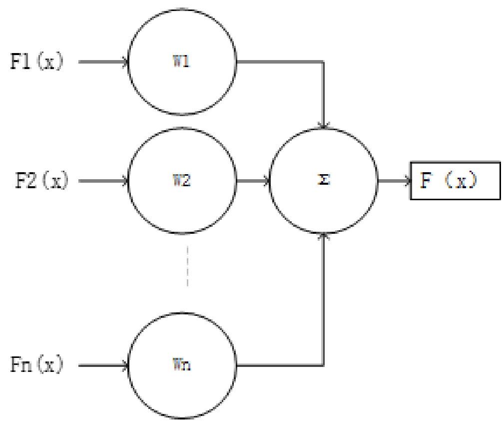

Fig.2. Principle diagram of weighted fusion algorithm

The adaptive weighting algorithm is a commonly used data fusion algorithm. Its characteristic is that it does not need to obtain the prior knowledge of the sensor. The fusion calculation can be performed only by the data measured by the sensor, and the result of the minimum mean square error is obtained. The weighted algorithm fusion schematic is shown in Figure 2:

For any two sensor forces p and q, there are measurement result signals X_p and X_q .eenerally speaking, these measurement results are composed of real signal X and observation errors V_P and V_q , denoted as $X_p = X + V_p$ and $X_q = X + V_q$. The observation errors V_P and V_q can be regarded as stationary noise with zero mean. Based on this, for any sensor p, the variance is, $\sigma_p^2 = E\left(V_P^2\right)$, where E (·)is the mean. Because the sensors are independent of each other, the observation error between the two sensors is not related, and the mean value of the observation error is 0 and not related to the real signal. The cross-correlation function R_{pq} between any sensor force p and q; the formula of the autocorrelation function R_{pp} R_{pp} of and any sensor p is as follows:

$$R_{pq} = E\left(X_p X_q\right) = E\left(X^2\right) \quad (6)$$

$$R_{pq} = E\left(X_p X_q\right) = E\left(X^2\right) + E\left(V_P^2\right) \quad (7)$$

In order to obtain the variance of any sensor, only the difference between its autocorrelation function and its cross-correlation function is needed. Since this paper uses multi-sensors to measure the signal, all functions need to be processed. In order to make the autocorrelation function and cross-correlation function as accurate as possible, the measurement data of each sampling point are averaged to obtain the autocorrelation function and cross-correlation function of the sensor, and then the measurement data of each sensor are averaged to obtain the cross-correlation function of the sensor. The calculation formula is as follows:

$$R_{pp}(k) = \frac{1}{k}\sum_{i=1}^{k} X_p(i)X_p(i) = \frac{k-1}{k}R_{pp}(k-1) + \frac{1}{k}X_p(k)X_p(k) \quad (8)$$

$$R_{pq}(k) = \frac{1}{k}\sum_{i=1}^{k} X_p(i)X_q(i) = \frac{k-1}{k}R_{pq}(k-1) + \frac{1}{k}X_p(k)X_q(k) \quad (9)$$

$$\bar{R}_{pq}(k) = \frac{1}{n-1}\sum_{q=1,q\neq 0}^{n} R_{pq}(k) \quad (10)$$

where n is the number of sensors; k is the number of sampling points; $R(k)$ is the correlation function of the sensor at time 4. The difference between $R_{pp}(k)$ and $\bar{R}_{pq}(k)$ is the estimation of the observation variance of the sensor p at the time of k. The formula of the unbiased estimation of the observation variance at the time of $\hat{\sigma}_p^2$, $\hat{\sigma}_p^2(k)$ is as follows:

$$\hat{\sigma}_p^2(k) = \frac{1}{k-1}\sum_{i=1}^{k} \hat{\sigma}_p^2(i) \tag{11}$$

Among them, $\hat{\sigma}_p^2(i)$ is the observation variance obtained from i sampling point. It should be noted that the larger the k is, the more accurate the variance estimation is.

After calculating the unbiased estimation of the observation variance of the sensor by using the formula (11), the sensor weight estimation $\hat{W}_p^*$ is obtained by using the following formula:

$$\hat{W}_p^* = \frac{1}{\sigma_p^2 \sum_{i=1}^{n} \frac{1}{\delta_i^2}} \tag{12}$$

Thus, the estimation of the sensor at the time point is as follows:

$$\hat{X} = \sum_{P=1}^{n} \hat{W}_p^* X_p(k) \tag{13}$$

In summary, the adaptive weighting algorithm is implemented in the following five steps

1) The autocorrelation function of the sensor at the time is obtained;
2) The cross-correlation function of the sensor at p time is obtained.
3) For any sensor, the variance is obtained by subtracting the autocorrelation function from the cross-correlation function.
4) Calculate the weight of each sensor by using the sensor variance;
5) Calculate the estimated value of the current moment by using the weight.

2.3. Kalman algorithm and adaptive weighted fusion algorithm characteristics analysis

The adaptive weighted fusion algorithm has strong adaptability, high accuracy, good real-time performance, and its structure is complex. The fusion of multi-sensor information image features has unique advantages. The learning of this algorithm provides a better idea for the fusion processing of single data. Kalman filter algorithm is a very mature data fusion algorithm for estimation. Its biggest advantage is that it not only filters out the noise of the measured signal, but also combines the previous estimation. Kalman filter is proved to be the optimal estimation in linear problems. The disadvantage is that the nonlinear effect is not the optimal estimation, and the linear environment needs to be set. Therefore, in our research, we consider that the UAV is a uniform linear decline process when it is close to the ground. Therefore, this paper obtains a better algorithm in line with this experiment through data acquisition, weight calculation and error comparison.

3. Analysis of experimental results

According to the calculation and analysis of the kalman fusion algorithm in Table 1 and the adaptive weighted fusion results in Table 2, it can be seen that after the data of the point and surface ranging sensors are fused by the two algorithms, the fused data have more accurate and reliable attributes, which are closer to the actual values.

After data fusion of point and surface ranging sensors, the advantages and disadvantages of kalman and adaptive weighted fusion algorithms are more obvious through data analysis. The trend graph of Kalman gain k in Kalman fusion can be approximately regarded as linear, so the weight of different sensors is also a linear process from far to near. Through the calculation of the experimental data, it can be determined that in the 50-450CM distance fusion, the closer the weight of the ultrasonic sensor is, the greater the laser sensor is. Therefore, this method has a good application in the process of collecting the accurate value of the acquisition distance in the close range of the UAV near the ground.

Table 1 Kalman algorithm measurement data of different sections and the corresponding variance, weighting factor and fusion results

sector	350-450	250-350	150-250	50-150
measured value	400	280	190	100
x1（k）	402.3	281.6	190.9	100.3
x2（k）	401.9	281.2	190.5	100.1
σ1（k）	2.3	1.6	0.9	0.3
σ2（k）	1.9	0.2	0.5	0.1
σ3（k）	1.47	0.96	0.44	0.09
$\sigma^2 1$（k）	5.29	2.56	0.81	0.09
$\sigma^2 2$（k）	3.61	1.44	0.25	0.01
$\sigma^2 3$（k）	2.15	0.92	0.19	0.009
ω1（k）	0.595	0.64	0.77	0.9
ω2（k）	0.405	0.36	0.23	0.1
kalman gaink	0.595	0.64	0.77	0.9
x^-（k）	402.062	281.344	190.592	100.12
error	+2.062	+1.344	+0.592	+0.12

Note: The units of the measured section, the measured value, the error, x1 (k) and x2 (k) in Table 1 are cm; x1 (k) is the measured value of the ultrasonic sensor, x2 (k) is the measured value of the laser sensor; σ1 (k), σ2 (k) and σ3 (k) are the standard deviation of ultrasonic sensor, laser sensor and fusion data. σ ^ 21 (k), σ ^ 22 (k) and σ ^ 23 (k) are variances of ultrasonic sensor, laser sensor and fused data respectively. ω1 (k) and ω2 (k) are the weight coefficients of ultrasonic sensor and laser sensor, respectively. x ^ - (k) is the result of kalman fusion, and the unit is cm.

Table 2 Adaptive weighted fusion algorithm measurement data and corresponding variance, weighting factor and fusion results

k	350-450	250-350	150-250	50-150
measured value	400	280	190	100
x1（k）	402.3	281.6	190.9	100.3
x2（k）	401.9	281.2	190.5	100.1
$\sigma^2 1$（k）	2.645	1.28	0.405	0.045

$\sigma^2 2(k)$	1.805	0.72	0.125	0.005
$\omega 1(k)$	0.5944	0.64	0.764	0.9
$\omega 2(k)$	0.4056	0.36	0.236	0.1
$x^{-}(k)$	402.129	281.344	190.806	100.12
error	+2.129	+1.344	+0.806	+0.12

Note: The units of the measured section, the measured value, the error, x1 (k) and x2 (k) in Table 2 are cm ; x1 (k) is the measured value of the ultrasonic sensor, x2 (k) is the measured value of the laser sensor ; σ ^ 21 (k) and σ ^ 22 (k) are the estimated values of measurement variance of ultrasonic sensor and laser sensor respectively. ω1 (k) and ω2 (k) are the weight coefficients of ultrasonic sensor and laser sensor, respectively. x ^ - (k) is the adaptive weighted fusion result, and the unit is cm.

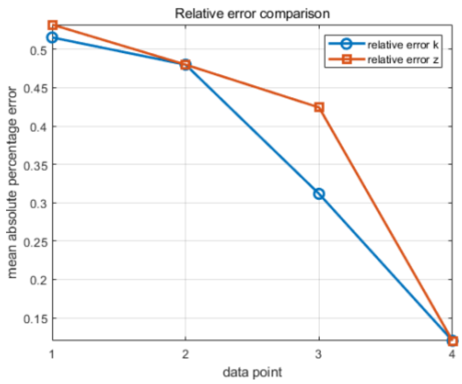

Fig.3.Comparison of fusion value and actual value

The whole data fusion process can be divided into three stages: 450 ~ 1500cm is measured by laser alone; laser and ultrasonic measurement of 50 ~ 450cm; ultrasonic measurement of 3-50cm alone. In this paper, multiple sets of different acquisition distances in the UAV near-ground ranging sensor system begin to be measured from 50 cm, and the true value is randomly measured once every 100 cm, until the distance from the target recognition is 400 cm. Tables 1 and 2 are partial measurement data and their fusion results.

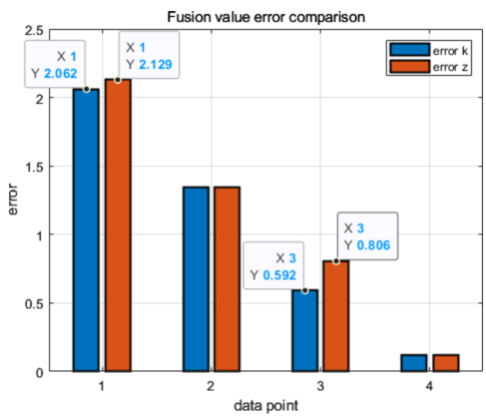

Fig 4. Comparison of fusion value error

It can be seen from Fig.1 and Fig.2 that after Kalman filter data fusion, the data error after fusion is smaller than that of adaptive weighted fusion, and the measured value after fusion is closer to the true value. According to the variance of each sensor, the respective weighting coefficients are obtained. The sensor with higher measurement accuracy has a higher weighting factor. With the increase of the number of times, the weighting factor is calculated according to the measurement data in each measurement. The importance of the weighting factor in the detection data processing is reflected by the weighting factor. The weighting factor changes with its measurement variance, and the measurement variance is estimated in real time by the measurement data of the sensor. Such Kalman fusion algorithm fully considers the environmental interference and ensures the real-time and accuracy of the measurement.

4. Conclusion

In this paper, data fusion is carried out based on point and surface ranging sensors. According to the complementary characteristics of point and surface sensors, the results of adaptive weighted fusion algorithm and kalman fusion algorithm are compared to compare the data fusion algorithm which is more suitable for point and surface sensors. The research results in this paper show that the data fusion of point and surface ranging sensors has more accurate specificity in data. The experimental scene is built to simulate the sensor to collect accurate data information, and the single type sensor and the fused data are compared respectively. The comparison results show that the weighted fusion based on Kalman filter algorithm can better improve the data accuracy and stability, and avoid the problem of mutation due to special circumstances. In view of the above research problems and experiments, this experiment uses the method of simulating the real scene to test the UAV ranging, so that it can use a more scientific data fusion method to collect the distance determination value, and at the same time, it has better application and development space in the agricultural UAV carrier.

In this paper, the surface sensor ultrasonic and the point sensor laser are used as the ranging system of the UAV near the ground. The laser sensor and the ultrasonic sensor detect the obstacles at the same time, which avoids the problem of reducing the real-time performance of the system and generating signal crosstalk due to the use of a single type of sensor for multiple measurements. The performance of the sensor and the appropriate algorithm is complementary, and the Kalman filter data fusion technology is used to obtain a more accurate distance estimate.

References

[1] Khan S, Tufail M, Khan M T, et al. Real-time recognition of spraying area for UAV sprayers using a deep learning approach[J]. Plos one, 2021, 16(4): e0249436.

[2] Aggarwal S, Kumar N. Path planning techniques for unmanned aerial vehicles: A review, solutions, and challenges[J]. Computer Communications, 2020, 149, p270-299.

[3] Chen H, Lan Y, Fritz B K, et al. Review of agricultural spraying technologies for plant protection using unmanned aerial vehicle (UAV)[J]. International Journal of Agricultural and Biological Engineering, 2021, 14(1), p38-49.

[4] Delavarpour N, Koparan C, Nowatzki J, et al. A Technical Study on UAV Characteristics for Precision Agriculture Applications and Associated Practical Challenges

[5] Kim S, Deshpande V M, Bhattacharya R. Robust Kalman filtering with probabilistic uncertainty in system parameters[J]. IEEE Control Systems Letters, 2020, 5(1), p295-300.

[6] Bao R, Huang L, Andrade J, et al. Review of current methods, applications, and data management for the bioinformatics

analysis of whole exome sequencing[J]. Cancer informatics, 2014, 13: CIN. S13779.

[7] Foxlin E. Inertial head-tracker sensor fusion by a complementary separate-bias Kalman filter[C]//Proceedings of the IEEE 1996 Virtual Reality Annual International Symposium. IEEE, 1996, p185-194.

[8] Li Yan, Zhang Qi, Wang Teng-jin. Research on Kalman Filter and Multisensor Data Fusion [J]. The Journal of New Industrialization, Vol. 9 (12), p96-100

[9] Hu Changlin,Sun Wei. Multi-sensor Data Fusion Performance Evaluation Indicatiors

[10] and Methods of Computation [J]. Modern Radar, 2013, 35 (03), p41-44+49

[11] Liang Yuming, Xu Lihong, Zhu Bingkun. Ranging Sensors Measurement Adaptive Weighted Fusion On － line [J]. Computer Measurement ＆ Control, 2009, 17 (07), p 1447-1449