A new state estimation approach-Adaptive Fading Cubature Kalman filter

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Abstract—This paper presents a novel adaptive fading cubature Kalman filter (AFCKF) based on double transitive factors. The developed adaptive algorithm is explained in two stages; stage (i) a single transitive factor is used to update the predicted state error covariance, \( \tilde{P}_k \), based on innovation or residual vector, whereas, in stage (ii), the measurement noise covariance matrix, \( \tilde{R}_k \), is scaled by another transitive factor. Furthermore, showing the proof concept for estimation of the process noise, \( \tilde{Q}_k \) and measurement noise covariance matrices by combining the innovation and residual vector in the AFCKF algorithm. It can provide reliable state estimation in the presence of unknown noise statistics. Bench-marking target tracking example is considered to show the performance improvement of the developed algorithms. As compared with existing adaptive approaches, the proposed fading algorithm can provide better estimation results.

Index Terms— Cubature Kalman filter, transitive factors, Innovation, sliding average method, Cubature Kalman filter, transitive factors, Innovation, sliding average method

I. INTRODUCTION

DIFF variants of nonlinear state estimators have been developed in the literature; Extended Kalman Filter (EKF) [1]. Unscented Kalman filter (UKF) [2] and cubature Kalman filter (CKF) [3] are the most popular methods. In the EKF, the non-linear function is approximated through Taylor or Jacobian calculations [4], whereas in the UKF [5] has been developed based on the sigma points approach. However, UKF has afforded considerably accurate estimation than the EKF estimator. But, the estimation accuracy of the UKF is limited for higher-order systems analysis. The CKF [3] can be developed and being widely applied into various real world estimation problems in [6], [7], [8], [9], [10], [11], [12].

System and measurement noise models may not known exactly and even vary with time in practice. However, the filter becomes divergence and the performance can be degraded. In [13], standard adaptive approaches have been developed in the literature; such as (i) Innovation Based Adaptive Estimation (IAE) and (ii) Residual Based Adaptive Estimation (RAE), (iii) multiple Model-Based Adaptive Estimation (MMAE) [14]. In adaptive estimation [15], estimation of the noise covariance matrices were developed neither residual nor innovation sequence in the first and second method, whereas, in the third approach, several filters are running in parallel, however, it causes an increment in the storage burden [16]. To realize in the MMAE, type of distribution of the innovation or residual vector must be known within a window for all epochs [17]. System uncertainty impact on filter performance and sub-optimal when the noise covariance matrices are varied under the fault measurements [17], [14]. By introducing the time-dependent variable, called fading factor, named it as Adaptive Fading Kalman Filter (AFKF) [18]. Non-linear fading EKF [1], [19], and adaptive fading AFUKF [20], adaptive fading cubature KF [4], [13]. The ACKF with a single fading factor was developed for estimating the noise covariance matrices. Technically, by using multiple fading factors (MFF) in the ACKF filter has more beneficial than the single fading factor-based AFKF, AFUKF [4] and AFCKF have the same performance, except in higher dimensional system estimation. The proposed methodology is developed based on double transitive factors and is the aim of this paper, that can correct the gain may be utilized by varying the predicted and measurement noise covariances. Best of author knowledge, there is a limited contribution on double transitive factors based nonlinear adaptive fading CKF algorithm. The contributions of this paper have the follows: This paper investigates the nonlinear state estimation problem by applying the adaptive fading cubature Kalman filter. An adaptive fading CKF framework is developed with double transitive factors. The state error covariance is adapted with a single transitive factor, then the process noise covariance matrix adaption is made by adjusting the properties of nonlinear systems. Another transitive factor is developed in this paper for scaling with the measurement noise covariance matrix adaption. Then, these errors are assumed to be non-Gaussian rather than satisfying the Gaussian distribution. A bench marking tracking example is shown to assess the performance improvement of the developed algorithm. The rest of the paper is organized as follows; the adaptive fading cubature Kalman filter based on double transitive factors is presented in Section II. In section III is shown the tracking example for validating proposed algorithms. The conclusion of the paper is presented in Section IV.

II. ADAPTIVE FADING CUBATURE KALMAN FILTER BASED ON DOUBLE TRANSITIVE FACTORS

A. Problem formulation

Considering the nonlinear discrete-time stochastic system, and measurement equations are

\[
x_k = f(x_{k-1}) + w_{k-1}
\]

(1)

\[
z_k = h(x_k) + v_k
\]

(2)

where, state vector, \( x_k \in \mathbb{R}^n \) with \( n \)-dimension and \( f(x_{k-1}) \) is the nonlinear function for the state, \( u_k \in \mathbb{R}^r \) is
considerable control input, and \(w_{k-1} \sim N(0, Q_k)\) the process is assumed to be Gaussian, the measurement vector \(z_k \in \mathbb{R}^m\) at time \(k\). The measurement nonlinear function \(h(x_k)\) and the measurement noise \(v_k \sim N(0, R_k)\) is also assumed to be Gaussian. Aim of this paper is develop a novel adaptive fading CKF based on double transitive factors. The recursive solution to the AFCKF algorithms for estimating noise statistics. The transitive factor, \((\alpha_1)\) for updating the predicted state error and double transitive factor, \((\alpha_2)\) for measurement noise covariance matrix. Furthermore, these covariance matrices are estimated by using innovation and residual vector difference. The detail derivations are explained in the following sub-sections [II-B] and [II-C].

**B. Adaptive fading CKF Scheme(AFCKF) for P-adaption**

In this section, innovative or residual sequence [13] is used to develop the adaptive fading CKF scheme for the predicted state error covariance adaption with defined single transitive factor, simply named it as AFCKF-P adaption algorithm. The innovation sequence is the difference between the measurement, \(z_k\) and predicted measurements, \(h(\hat{x}_k)\), is defined as

\[
\nu_k = z_k - h(\hat{x}_k)
\]  

(3)

By considering the measurement equation into equation (3) and applying the expectation on both sides, we can get the auto-covariance of the innovation sequence is

\[
E[\nu_k \nu_k^T] = E[h(x_k - \hat{x}_k) + v_k][h(x_k - \hat{x}_k) + v_k]^T
\]

\[
= E[h(\Delta \hat{x}_k) + v_k][h(\Delta \hat{x}_k) + v_k]^T
\]

\[
= hE[(\Delta \hat{x}_k)(\Delta \hat{x}_k)^T]^h + E[v_k v_k^T]
\]

\[
= h\hat{P}_k h^T + R_k
\]

\[
= \sum_{i=0}^{2L} W_i^T (\hat{z}_k - \bar{z}_k)(\hat{z}_k - \bar{z}_k)^T + R_k
\]

\[
= C_{\nu k}
\]  

(4)

where, \(C_{\nu k}\) is the theoretical covariance matrix of the innovation sequence, \(x_k\) and \(x_k\) are the predicted and estimated states. \(W_i^T\) is the weights, \(L\) is the dimension of the state vector, \(\Delta \hat{x}_k\) error between actual and estimated states. \(T\) is the transpose. Furthermore, the estimated covariance matrix of innovation through windowing average method [13] is

\[
\hat{C}_{\nu k} = \frac{1}{N_w} \sum_{j=0}^{k} \tilde{\nu}_j \tilde{\nu}_j^T
\]  

(5)

where \(N_w\) is the moving window width. As it is known, when the sample window, \(N_w\) increases the sample covariance tends to close to the actual value. However, it satisfies the stationary processes, whereas in the non-stationary conditions, the true innovation-covariance matrix varying with time at each epoch. The selection of transitive factor \(a_1(k)\) is evaluated as

\[
a_1(k) = \begin{cases} 1, & \text{if } tr(\hat{C}_{\nu k}) > tr(\hat{P}_{\nu k}) \\ \frac{tr(\hat{C}_{\nu k} - R_k)}{tr(\hat{P}_{\nu k} - R_k)}, & \text{otherwise.} \end{cases}
\]

with \(a_1(k)\) being a adaptive transitive factor, this value is varied accord to the actual and estimated covariance matrices of the innovation vector, \(\nu_k\). Here, \(tr\) is the trace function. If the are larger than that of actual values, \(a_1(k)\). Otherwise, \(a_1(k)\) is approximately calculated the ratio difference of estimated covariance matrix of the innovation sequence and measurement noise covariance matrix.

The predicted state covariance \(\hat{P}_k\) is scaled by a single transitive factor [21]

\[
\hat{P}_k = \frac{1}{a_1(k)} \hat{P}_{k-1}
\]  

(6)

Generally the predicted state error covariance as in (6) and is evaluated from the innovation samples. The \(\hat{P}_k\) should satisfy the symmetric and positive semi-definite at each time step. The state error covariance is adaptively updated with the transitive factor and then it can be used into the Q adaption (see in Theorem 1). In this stage, error variation in the state models due to the fault measurements, thus, the AFCKF-prediction equation is inaccurate, and causing to increase the error covariance and consequently of Kalman gain. Therefore, introducing another adaptive transitive factor in the following subsection, which takes to quickly react to the state variation.

**C. Adaptive fading CKF Scheme(AFCKF)-R adaption**

Once we update the optimal transitive factor in stage I, then it can forward to second stage II. The AFCKF algorithm, the measurement noise covariance matrix is scaled by the double transitive factor, named it as AFCKF-R adaption. The transitive factor \(a_2(k)\) is evaluated as

\[
a_2(k) = \begin{cases} 1, & \text{if } tr(\hat{C}_{\nu k}) > tr(\hat{P}_{\nu k}) \\ \frac{tr(\hat{C}_{\nu k} - R_k)}{tr(\hat{P}_{\nu k} - R_k)}, & \text{otherwise.} \end{cases}
\]

where \(\hat{P}_{\nu k} = \eta_k \nu_k^T\) is the estimated covariance matrix of the residual sequence. The double transitive factor \(a_2(k)\) is used to multiply with the measurement noise covariance matrix. Thus, equation (7) can be written as

\[
P_{z_k} = \sum_{i=0}^{2L} W_i^T ([Z_k]_i - \bar{z}_k)([Z_k]_i - \bar{z}_k)^T + a_2(k)R_k
\]  

(7)

The relation between \(a_2(k)\) and \(R_k\) are proportional. If \(a_2(k)\) is large, \(R_k\) also becomes larger, which means the Kalman gain is less and then the influence of uncertainty is more we can trust more on the measurements, other wise versa [21]. In the section A (AUFK-F-P adaption algorithm) predicted state error covariance and B (AUFK-F-R adaption algorithm) measurement noise covariance matrix are adapted with double factor and is given in theorem 1.

**Theorem 1.** Suppose the noise statistics of the process and measurement noise parameters are very small within a considerable window size of \(N_w\). Then, a novel process noise statistic estimators are estimated with difference of innovation and residual vector and transitive factor, and then \(a_1(k)\) in the predicted state error covariance, \(Q_k\) is developed. Moreover,
$a_2(k)$ in the measurement noise covariance is estimated, $R_k$ are derived as

$$h\tilde{Q}_{k-j}h^T = \frac{1}{N_w} \sum_{j=1}^{N_w} (v_k - \eta_j)(v_k - \eta_j)^T$$

$$- h\left(\frac{1}{2L} \sum_{i=1}^{2L} (X_k - \bar{x}_i)(X_k - \bar{x}_i)^T \right)\right) + h\hat{P}_k h^T$$

$$\hat{R}_{k-j} = \frac{1}{N_w} \sum_{j=0}^{N_w} v_j^T - h\hat{x}_{k-j} h\hat{x}_{k-j}$$

(8)

Proof. Let us assume that the process and measurement co-variances of noise statistics are varies from $l_k - N_w$ to $l_k$, the window width, $N_w$ and there are $N_w$ measurements. The innovation and residual sequence are represented already in equation (9) and (10). By defining predicted and estimated state errors [22] are

$$\Delta \hat{x}_k = x_k - \hat{x}_k$$

$$\tilde{x}_k = x_k - \hat{x}_k$$

(9)

As per expectation and correlation definition, if the process and measurement noises are uncorrelated, then $E[(\Delta \tilde{x}_k)v_k]\mathbf{T}] = 0$. We can also check cross-correlation of $E[(\Delta \tilde{x}_k)(\Delta \hat{x}_k)^T]$ and $[v_k(\Delta \tilde{x}_k)^T]$, we have

$$E[\eta_k\eta_k^T] = E[h(x_k - \hat{x}_k) + v_k]\mathbf{T} = E[h(\Delta \tilde{x}_k) + v_k]\mathbf{T}$$

$$= h\tilde{x}_k^T + E[\Delta \tilde{x}_k]\mathbf{T} - h\tilde{P}_k h^T$$

(10)

By considering the cross correlation between residual and innovation sequence. Then, we can rewrite equation are

$$E[\eta_k\epsilon_k^T] = E[h(x_k - \hat{x}_k) + v_k]\mathbf{T} = E[h(\Delta \tilde{x}_k) + v_k]\mathbf{T}$$

$$= h\tilde{x}_k^T + E[\Delta \tilde{x}_k]\mathbf{T} + hE[(\Delta \tilde{x}_k)^T] + E[\tilde{x}_k]\mathbf{T}$$

$$+ h\tilde{Q}_{k-j}h^T$$

(11)

By taking the difference between innovation and residual and then applying the expectation for them is as follows that Equation (18) and (21), the innovation and residual covariance, and substitute the predicted state error covariance inside the equations, rewrite the equation as

$$E[(v_k - \eta_k)(v_k - \eta_k)^T] = E[v_k v_k^T] + E[\eta_k\eta_k^T]$$

$$+ E[v_k\epsilon_k^T] + E[\epsilon_k\epsilon_k^T]$$

$$= h\hat{P}_{k-1} h^T + R_k + R_k - h\hat{P}_k h^T$$

$$- 2(h\hat{P}_k h^T + R_k h\hat{K}_k h^T + R_k)$$

$$= h\hat{P}_{k-1} h^T - h\hat{P}_k h^T$$

$$= h\left(\frac{1}{2L} \sum_{i=1}^{2L} (X_k - \bar{x}_i)(X_k - \bar{x}_i)^T \right)$$

$$- \hat{x}_{k-1}\hat{x}_{k-1}^T + Q_{k-1} h^T - h\hat{P}_k h^T$$

(12)

We can separate out the process noise covariance matrix from the above equations.

$$h\tilde{Q}_{k-1} h^T = E[(v_k - \eta_k)(v_k - \eta_k)^T]$$

$$- h\left(\frac{1}{2L} \sum_{i=1}^{2L} (X_k - \bar{x}_i)(X_k - \bar{x}_i)^T \right)\right)$$

$$+ h\hat{P}_k h^T$$

(13)

On the other hand, the above equation can be approximate the limited number of sample for the difference of innovation and residual sequence is

$$h\tilde{Q}_{k-1} h^T = \frac{1}{N_w} \sum_{j=1}^{N_w} (v_k - \eta_j)(v_k - \eta_j)^T$$

$$- h\left(\frac{1}{2L} \sum_{i=1}^{2L} (X_k - \bar{x}_i)(X_k - \bar{x}_i)^T \right)\right)$$

$$+ h\hat{P}_k h^T$$

(14)

According to equation (11) and applying the cross-correlation for equation (13) and (11) at each epoch. By taking a limited number of sample of the innovation sequence in terms of mean and the covariances are

$$\tilde{v}_k = \frac{1}{N_w} \sum_{j=1}^{N_w} v_k - \eta_j$$

(15)

$$E[v_k v_k^T] = \frac{1}{N_w - 1} \sum_{j=1}^{N_w} (v_k - \tilde{v}_k)^T(v_k - \tilde{v}_k)$$

The combination of innovation and residual sequence is used to improve the Q estimation, in term of robustness. By considering the sample covariance, thus, the predicted state error covariance is equal to

$$\hat{P}_{k-1}^{-1} = \frac{1}{a_1(k)} \left[ \frac{1}{2L} \sum_{i=1}^{2L} (X_k - \bar{x}_i)(X_k - \bar{x}_i)^T - \hat{x}_{k-1}\hat{x}_{k-1}^T \right]$$

$$+ h\tilde{Q}_{k-1} h^T$$

(16)

Similarly, we can applying the sample sequence of residual vector as

$$\hat{R}_{k-j} = \frac{1}{N_w} \sum_{j=0}^{k} \eta_j \eta_j^T - \frac{1}{2L} \sum_{i=1}^{2L} (Z_k - \bar{z}_i)(Z_k - \bar{z}_i)^T - \hat{z}_{k-1}\hat{z}_{k-1}^T$$

(17)
and thus, the auto covariance of residual sequence $P_{z_k,k}$ is evaluated as

$$P_{z_k,k} = \sum_{i=0}^{2L} W_i^* [(Z_k)_i - \hat{z}_k^-][(Z_k)_i - \hat{z}_k^-]^T + a_2(k)R_k^*$$  \hspace{1cm} (18)

The equations (14) and (17) are the completes the proof.

The pseudo-code of the proposed strategy is given in Algorithm 1.

**Algorithm 1** AFCKF for P and R adaption

1. **Input:** Initialize the $\hat{x}_0, P_0, Q_0, R_0$
2. **Compute:** $\xi_i \leftarrow \sqrt{L[1]}_i, W_i \leftarrow \frac{1}{\pi}$
3. **for** $k = 1$ to $N$ **do**
4. **Time update:**
5.  $\hat{x}_{k-1} \leftarrow \frac{1}{\pi} \sum_{i=1}^{2L} (X_{k-1})_i$
6. **Compute single transitive factor:**
7.  $a_1(k) = \begin{cases} \frac{1}{tr(\hat{\xi}_k)} & \text{if } tr(P_{z_k,k}) > tr(\hat{\xi}_k) \\ \frac{1}{tr(C_{\xi}^k)} & \text{otherwise} \end{cases}$
8.  $\hat{P}_{k-1} \leftarrow a_1(k) \left( \frac{1}{\pi} \sum_{i=1}^{2L} (X_{k-1})_i(X_{k-1})_i^T - \hat{x}_{k-1}\hat{x}_{k-1}^T + Q_{k-1} \right)$
9.  $\hat{z}_{k-1} \leftarrow \frac{1}{\pi} \sum_{i=1}^{2L} (Z_{k-1})_i$
10. **Measurement update:**
11. $K_k \leftarrow P_{z_k,k-1}P_{z_k,k}^{-1}$
12. $\hat{x}_k \leftarrow \hat{x}_{k-1} + K_k(z_k - \hat{z}_{k-1})$
13. $\hat{P}_k \leftarrow \hat{P}_{k-1} - K_kP_{z_k,k-1}K_k^T$
14. **Compute double transitive factor:**
15.  $a_1(k) = \begin{cases} \frac{1}{tr(\hat{\xi}_k)} & \text{if } tr(P_{z_k,k}) > tr(\hat{\xi}_k) \\ \frac{1}{tr(C_{\xi}^k)} & \text{otherwise} \end{cases}$
16.  $P_{z_k,k-1} \leftarrow \frac{1}{\pi} \sum_{i=1}^{2L} (Z_{k-1})_i(Z_{k-1})_i^T - \hat{x}_{k-1}\hat{x}_{k-1}^T$
17.  $P_{z_k,k-1} \leftarrow \frac{1}{\pi} \sum_{i=1}^{2L} (Z_{k-1})_i(Z_{k-1})_i^T - \hat{z}_{k-1}\hat{z}_{k-1}^T + a_1(k)R_k^*$
18. **end for**
19. **Output:** $\hat{x}_k, \hat{P}_k, \hat{Q}_k, \hat{P}_k, a_1(k), a_2(k)$

The pseudo code for adaptive fading algorithm for $Q_k^*$ and $R_k^*$ is shown in Algorithm 1 and 2, respectively. Note that, we have consider only R-estimation for simulation analysis.

### III. Simulation Results

Simulation study of a bench-marking target tracking example [23] is presented in this section for comparing the performance assessment of the proposed algorithm with the existed algorithms; the CKF, ACKF, AFCKF- P adaption approaches. The nonlinear system and measurement models for target tracking example can be expressed as follows [6], [22]. The state vector, $x_k = [x_{1,k} \ x_{2,k} \ x_{3,k} \ x_{4,k}]^T$ including the vehicle position and velocity in x and y-plane. $T_s = 0.1s$ is the step size. The process, $Q_k$ and measurement $R_k$ noise covariance matrices are initialized as $Q_0 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 2 \times 10^{-1} & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$, $R_0 = \begin{bmatrix} 100 & 0 \\ 0 & 3 \times 10^{-4} \end{bmatrix}$

In this section, we consider two different cases for the measurement noises variations as the following: Case A: under Gaussian distribution, Case B: under unknown time-varying measurement noise covariance. The proposed algorithm is compared with other nonlinear cubature filters are implemented including the CKF, ACKF, AFCKF, AFCKF-P adaption. Fig. 1 shows the position estimation of target tracking is obtained. During 4-6 sec, it can be seen that all algorithms can track the actual state, then after the AFCKF-R adaption algorithm has a small deviation from the actual position due to Q value. Subsequently, vehicle seed is better than the other nonlinear approaches. However, the proposed algorithms have better tracking ability in the position estimation when system and measurement model noise change.

The RMSE of position and velocity error are shown in Fig. 2 and 3, respectively. It can be seen that the proposed AFCKF-R adaption algorithms yield better estimation accuracy than the non-adaptive CKF and adaptive approaches. Overall, the proposed AFCKF methods are particularly useful for target tracking state estimation under unknown ambient noises. The average RMSE values of CKF, ACKF and AFCKF algorithms are 1.72m, 0.70m and 0.55m, respectively. However, AFCKF-R adaption algorithm outperforms the CKF, ACKF, AFCKF, and AFCKF-P adaption as well.

**Table I:** Average RMSE of considered algorithms

|           | Case A RMSE[m] | RMSE[m/s] | Case B RMSE[m] | RMSE[m/s] |
|-----------|---------------|-----------|----------------|-----------|
| CKF[3]    | 1.72          | 2.30      | 1.75           | 2.50      |
| ACKF[19]  | 0.71          | 1.93      | 0.74           | 1.93      |
| AFCKF[6]  | 0.55          | 1.02      | 0.54           | 0.53      |
| AFCKF-P   | 0.52          | 0.23      | 0.35           | 0.32      |
| AFCKF-R   | 0.12          | 0.21      | 0.24           | 0.11      |

**Table I:** Average RMSE of considered algorithms

Figure 1: Target tracking result for position and its estimation.
The AFCKF-R adaption method can track the true trajectory. Based on the results, it is obvious that two proposed algorithms, AFCKF-P and R adaption methods provide the best results than non-linear filters. The AFCKF-R adaption can obtain better accuracy than the AFCKF-P adaption algorithm under the considerable case A and also more accurate under the time-varying measurement noise, other considerable case B.

IV. Conclusion

The summary of the paper is as follows; the AFCKF algorithm is developed based on the double transitive factors. In which, the noise covariance matrices are estimated difference between the innovation and residual sequence. The developed algorithm with $R^2_\xi$ estimation is only applied in the application of target tracking . The proposed algorithm could solve the problem of better positioning accuracy, quick converge in the position and velocity, and also to make it better tracking. The RMSE values of considerable algorithms are observed that approximately 20% in position and 30% in velocity are improved. Compared with the traditional CKF, ACKF and AFCKF algorithms, the proposed approach has a better adaptability with the time-varying noise covariance.

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