Performance Monitoring of Nonlinear CSTR Using Novel Adaptive Unscented Kalman Filter

Lotfollah Jargani, Mehdi Shahbazian, Karim Salashoor, Vahid Fathabadi

***Abstract*- This paper investigates the application of multi-sensor data fusion (MSDF) technique to enhance the state estimation of a nonlinear plant. The proposed method is based on Kalman filters approach to improve the state estimation obtained by the adaptive unscented Kalman filter (AUKF). In order to prevent estimation algorithm to diverge caused by pre-specified fixed distribution matrices assumed by UKF, a novel adaptive unscented Kalman filter algorithm has been presented in this paper. Here, however, variance matrices for both process and measurement noise signals are assumed unknown *a priori* and thus incrementally estimated and updated using a sliding time window paradigm within which an estimation of the noise variance is calculated and adaptively updated each time the window is shifted forward. The proposed methodology is tested on a simulated continuous stirred tank reactor (CSTR) problem to estimate 4 states of this nonlinear plant. The simulation results demonstrate the superiority of the suggested method in state estimation compared with the classical UKF-based approach.**

***Keywords*: Multi-sensor data fusion, Unscented Kalman filter, Centralized Kalman filter, State estimation.**

I. Introduction

Data fusion is a multilevel, multifaceted process dealing with the detection, association, correlation, estimation and combination of data and information from multiple sources to achieve refined state and identity estimation, and complete and timely assessments of situation and threat. The use of multiple sensors allows the data of one sensor to complement that of another sensor in order to extract the greatest amount of information about the sensed environment [1]. Among the various techniques available for multi-sensor data fusion, Kalman filtering-based approach is one of the most significant one, as it proves to be an efficient recursive algorithm suitable for real-time applications. Kalman filtering is used in many fields such as control, communication, data assimilation, and target tracking.

It is the optimal filter for linear systems with known noise statistical characteristics. Extended Kalman filter as a widely used approach in nonlinear systems, use the first order Taylor series to transform nonlinear system to linear system.

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A recent improvement to the EKF is the unscented Kalman filter (UKF) [2]. The UKF approximates the probability density resulting from the non-linear transformation of a random variable instead of approximating the nonlinear functions with a Taylor series expansion. The approximation is done by evaluating the nonlinear function with a minimal set of carefully chosen sample points. The posterior mean and covariance estimated from the sample points are accurate to the second order for any nonlinearity [3]. If the priori random variable is Gaussian, the posterior mean and covariance are accurate to the third order for any nonlinearity [4].

All these Kalman filters are used for known noise statistical characteristics. When these statistics are unknown, however, we must use adaptive Kalman filters. We may use adaptive Kalman filter banks for weight to compute covariance [5], or output correlation to compute Kalman gain without care for these covariance [6], or fading memory algorithm to reduce the effect of prior measurement [7]. These approaches, however, can only be used in linear systems, and reveal poor performances for the case of nonlinear systems.

A novel adaptive Unscented Kalman filter (AUKF) is presented in this paper. The main idea of this method is to approximate noise variance by employing a sliding time window within which an estimation of the noise variance is calculated and adaptively updated each time the window is shifted forward.

This paper is organized as follows. In section 2, the proposed methodology is presented. Section 3 describes the CSTR case study. The effectiveness of the proposed approach is demonstrated in section 4. Finally, the conclusions are given in section 5.

II. Proposed Methodology

Multi-sensor data fusion is concerned with the integration and extraction of information from data obtained by two or more sensors. In many processes, data from multiple sensors must be fused to obtain more complete and more accurate information about the operation.

Among the various techniques available for multi-sensor date fusion, Kalman filtering-based approach is one of the most significant one, as it proves to be an efficient recursive algorithm suitable for real-time applications. State-vector fusion and measurement fusion are two commonly employed methods for Kalman filter-based sensor fusion [8].

As shown in fig.1(b), state-vector fusion method uses a group of Kalman filters to obtain individual sensor-based state estimates which are then fused to get an improved joint state estimate. On the other hand, the measurement fusion method

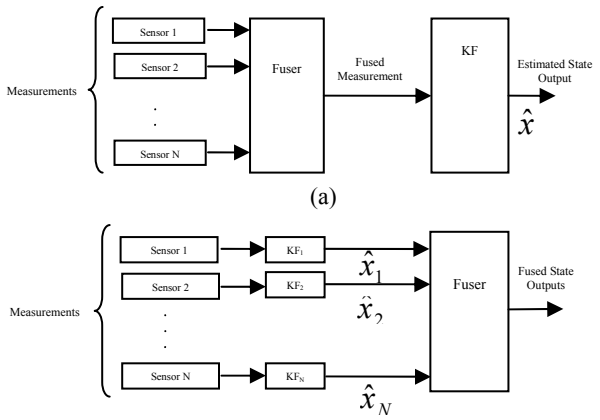

Figure 1. Kalman-filter-based multi-sensor data fusion. (a) Measurement fusion (b) state-vector fusion.

in fig.1(a), to obtain a weighted or combined measurement and then uses a single Kalman filter to get the final state estimate based on the fused measurement. Both methods have their own merits and demerits. The measurement fusion method requires that the sensor should have identical measurement matrices (H). Although the measurement fusion method provides better overall estimation performance, state-vector fusion has lower computational cost and possesses the advantage of distributed parallel computation and fault tolerance. Judicious trade-off between computational complexity, comutatioal time and numerical accuracy has to be made for selection of the proper algorithm for any practical application.

In this work, the measurement fusion technique has been adopted for fusing multiple sensors to provide necessary information to enhance the AUKF estimation.

A. Unscented Kalman Filter

In 1960, R.E. Kalman published his famous paper describing a recursive solution to the discrete-data linear filtering problem. Kalman filter algorithm attempts to propagate the mean and covariance of a system using a time-update and a measurement update. If the system is linear, then the mean and covariance can be exactly updated with the Kalman filter. If the system is nonlinear, then the mean and covariance can be approximately updated with the extended Kalman filter. The extended Kalman filter (EKF) is the most widely applied state estimation algorithm for nonlinear systems. However, the EKF can be difficult to tune and often gives unreliable estimates if the system nonlinearities are severe. This is because the EKF relies on linearization to propagate the mean and covariance of the state.

Julier and Uhlman developed the UKF algorithm[9]-[10], they used the unscented transform to compute the statistical characteristics of states and measurements, for the unscented transform is second-order equal to the real statistics at least. An unscented transformation is based on two fundamental principles. First, it is easy to perform a nonlinear transformation on a single point (rather than an entire pdf). Second, it is not too hard to find a set of individual points in state space whose sample pdf approximates the true pdf of a state vector.

Taking these two ideas together, suppose that we know the mean $\bar{x}$ and covariance P of a vector x. A set of deterministic vectors called sigma points whose ensemble mean and covariance are equal to $\bar{x}$ and P can be find. We next apply our known nonlinear function $y = h(x)$ to each deterministic vector to obtain transformed vectors. The ensemble mean and covariance of the transformed vectors will give a good estimate of the true mean and covariance of y. This is the key to the unscented transformation. The UKF algorithm can be simply obtain by replacing the EKF equations with unscented transformations [11]-[14].

Suppose the nonlinear system equations obey the following non-linear relationships:

$$x_k = f_{k-1}(x_{k-1}, u_{k-1}) + w_{k-1} \tag{1}$$

$$y_k = h_k(x_k) + v_k \tag{2}$$

$$w_k \sim (0, Q_k) \tag{3}$$

$$v_k \sim (0, R_k) \tag{4}$$

w_k and v_k are process noise and measurement noise with variances of $Q_k$and R_k respectively. n and m signifies number of states and outputs .

The UKF algorithm can be summarized as follows:

1- The algorithm will be started with some initial guesses for the state estimation (x_0) and the error covariance matrix (P_0), defined as:

$$\hat{x}_0^+ = E[x_0] \tag{5}$$

$$P_0^+ = E[(x_0 - \hat{x}_0^+)(x_0 - \hat{x}_0^+)^T] \tag{6}$$

2- The following time update equations are used to propagate the state estimate and covariance from one measurement time to the next:

(a) Calculate a collection of sigma points, stored in the columns of the $n \times (2n + 1)$ sigma point matrix $\hat{x}_{k-1}^+$ as:

$$\chi_{k-1} = \left[\hat{x}_{k-1}^+ \quad \hat{x}_{k-1}^+ + \sqrt{(n+\lambda)P_{k-1}^+} \quad \hat{x}_{k-1}^+ - \sqrt{(n+\lambda)P_{k-1}^+}\right] \tag{7}$$

The parameter is a scaling parameter defined as:

$$\lambda = \alpha^2(n + \kappa) - n \tag{8}$$

The constant α determines the spread of the sigma points around $\hat{x}_{k-1}^+$ and κ is a secondary scaling parameter.

(b) Propagate each column of χ_{k-1}(i.e.,χ_{k-1}^i) through the nonlinear system dynamic equation to perform the prediction or time update step as:

$$\chi_{k-1}^{*,i} = f(\chi_{k-1}^{i}, u_{k-1}) \quad i = 0,1,\cdots,2n \tag{9}$$

$$\chi_{k-1}^{*} = f(\chi_{k-1}, u_{k-1}) \tag{10}$$

(c) Then a priori estimate values for state and error covariance are calculated as:

$$\hat{x}_k^- = \sum_{i=0}^{2n} W_i^{(m)} \chi_{k-1}^{*,i} \tag{11}$$

$$P_k^- = \sum_{i=0}^{2n} W_i^{(c)} (\chi_{k-1}^{*,i} - \hat{x}_k^-)(\chi_{k-1}^{*,i} - \hat{x}_k^-)^T + Q_{k-1} \tag{12}$$

Where $W_i^{(m)}$ and $W_i^{(c)}$ are sets of scalar weights defined by:

$$W_0^{(m)} = \frac{\lambda}{\lambda+n} \tag{13}$$

$$W_0^{(c)} = \frac{\lambda}{\lambda+n} + (1 - \alpha^2 + \beta) \tag{14}$$

$$W_i^{(m)} = W_i^{(c)} = \frac{1}{2(\lambda+n)} \quad i = 1,\cdots,2n \tag{15}$$

β is a parameter used to incorporate any prior knowledge about the distribution of x.
3- Now that the time update equations are done, we implement the measurement-update equations.
(a) The sigma points are updated as:

$$\chi_{k|k-1} = \left[\hat{x}_k^- \quad \hat{x}_k^- + \sqrt{(n+\lambda)P_k^-} \quad \hat{x}_k^- - \sqrt{(n+\lambda)P_k^-}\right] \tag{16}$$

(b) Propagate each column of $\chi_{k|k-1}$through the nonlinear system measurement equation to predict the measurement values as:

$$\hat{y}_k^{(i)} = h(\chi_{k|k-1}^{i}) \tag{17}$$

$$\hat{y}_k = \sum_{i=0}^{2n} W_i^{(m)} \hat{y}_k^{(i)} \tag{18}$$

(c) After the prediction step, the correction or measurement update step is performed to calculate the posterior estimate state as follows:

$$\hat{x}_k^+ = \hat{x}_k^- + K_k(y_k - \hat{y}_k) \tag{19}$$

Where y_k is the actual measurement vector. The y_k can be pre-filtered with a simple Kalman filter (KF) with identity gain and unit observation gain. This pre-filter removes the Gaussian noises much extent and helps the UKF algorithm for better convergence and less deviations in the final estimated states. K_k is the Kalman gain defined by:

$$K_k = P_{xy} P_y^{-1} \tag{20}$$

Where

$$P_{xy} = \sum_{i=0}^{2n} W_i^{(c)} (\chi_{k|k-1}^{i} - \hat{x}_k^-)(\hat{y}_k^{(i)} - \hat{y}_k)^T \tag{21}$$

$$P_y = \sum_{i=0}^{2n} W_i^{(c)} (\hat{y}_k^{(i)} - \hat{y}_k)(\hat{y}_k^{(i)} - \hat{y}_k)^T + R_k \tag{22}$$

$$P_k^+ = P_k^- - K_k P_y K_k^T \tag{23}$$

B. Adaptive Unscented Kalman Filter

The theory presented in section 2.A makes the Kalman filter an attractive choice for state estimation. But when a Kalman filter is implemented on a real system it may not work, even though the theory is correct. Two of the primary causes for the failure of Kalman filtering are finite precision arithmetic and modeling errors [15].

The theory presented also assumes that the system model is precisely known. It is assumed that the noise sequences $\{w_k\}$ and $\{Q\}$ are pure white, zero-mean, and completely uncorrelated. If any of these assumptions are violated, as they always are in real implementations, then the Kalman filter assumptions are violated and the theory may not work. In order to improve filter performance in the face of these realities, the following methods are presented.

1) Fading Method :

It is a simple way of forcing the filter to "forget" measurements in the distant past and place more emphasis on recent measurements. This causes the filter to be more responsive to measurements. It theoretically results in the loss of optimality of the Kalman filter, but it may restore convergence and stability. It is better to have a theoretically suboptimal filter that works rather than a theoretically optimal filter that does not work due to modeling errors. The greater responsiveness of the fading-memory filter to recent measurements makes the filter less sensitive to modeling errors, and hence more robust. The main part of fading is updating covariance for each step $k = 1,2,\cdots$ as below:

$$P_k^+ = \alpha^2 P_k^+ \qquad \alpha > 1 \tag{24}$$

Note that P is not equal to the covariance of the estimation error. However, the fading-memory filter is more robust to modeling errors than the standard Kalman filter. If $\alpha = 1$ then the fading-memory filter is equivalent to the standard Kalman filter. In most applications, α is only slightly greater than one based on how much past measurements should be forgotten.

2) Novel Adaptive Method

As discussed earlier, KF methods assume that the exact value of measurement and process noise variances are known.

However, basically, in real industrial processes, it is not a very practical assumption. Thus, an adaptive method that can estimate the process and measurement noise variances could help to make the assumptions more realistic. Authors suggestion for updating procedure based on the fact that process and measurement noise variances are in fact unknown can be formulated as follows.

Suppose the dynamic system equation is

$$x_k = f_{k-1}(x_{k-1}, u_{k-1}, t_{k-1}) + w_{k-1} \quad (25)$$

$$\hat{x}_k^- = f_{k-1}(\hat{x}_{k-1}^+, u_{k-1}, t_{k-1}) \quad (26)$$

Where $\hat{x}_k^-$ indicates the calculated state using time-update equations and $\hat{x}_k^+$ shows the estimated state using measurement-update equations. Generally, $\hat{x}_k^+$ is more accurate than $\hat{x}_k^-$ due to the fact that the measurement of time K in estimation node is considered in the procedure.
Consider $\hat{x}_k^+$ is sufficiently close to x_k. Hence, following the Eqs. (26) and (27), the process noise could be estimated as the difference between $\hat{x}_k^+$,$\hat{x}_k^-$ i.e. $\widehat{w}_{k-1} = \hat{x}_k^+ - \hat{x}_k^-$. Consequently, the process noise variance ($\widehat{Q}_{k-1}$) could be obtained via Eq. (28).

$$\widehat{w}_{k-1} = \hat{x}_k^+ - \hat{x}_k^- \quad (27)$$

$$\widehat{Q}_{k-1} = E\left[\widehat{w}_{k-1}\widehat{w}_{k-1}^T\right] \quad (28)$$

Q_k was assumed to be diagonal, thus, its estimation $\widehat{Q}_k$ should also be diagonal.

$$\widehat{Q}_{k-1} = \mathrm{diag}[DVQ] \quad (29)$$

Process noise can be computed using a limited preceding horizon.

$$DVQ_i = \frac{1}{M-1}\sum_{j=1}^{M} \widehat{w}_{i,k-j}\widehat{w}_{i,k-j} \qquad i = 1,2,\cdots,n \quad (30)$$

M signifies to the length of the window size. Applying Eqns. (29) and (30), the process variance noise can be estimated using previous available data.

The variance of measurement noise should be estimated as well. Generally, the covariance matrix is determined using Eq. (31).

$$P_k = E[(x_k - \hat{x}_k)(x_k - \hat{x}_k)^T] \quad (31)$$

η_k and ε_k are defined as error in each time-step

$$\eta_k = y_k - H_k\hat{x}_k^- \quad (32)$$

$$\varepsilon_k = y_k - H_k\hat{x}_k^+ \quad (33)$$

In order to estimate the measurement noise, an innovation step is here introduced by authors. In this step, the measurement noise is computed using a new introduced sequence IS . IS is defined in Eqs. (34), (35) and (36).

$$IS_{2k-1} = \eta_k \, , IS_{2k} = \varepsilon_k \quad (34)$$

$$IS = y - H\hat{x} \quad (35)$$

$$IS = (Hx_k + v_k) - H\hat{x}_k = v_k + H(x_k - \hat{x}_k) \quad (36)$$

Where H represents for $\frac{\partial h_k(x_k)}{\partial x_k}$ that in most practical applications is a constant matrix. In order to find the relationship between IS and actual measurement noise R_k, the variance of IS should be computed. If v_k and $\hat{x}_k$ be independent, $E[IS\ IS^T]$can be calculated using Eq. (37).

$$E[IS\ IS^T] = R_k + HP_kH^T \quad (37)$$

However, v_k and $\hat{x}_k$ are not really independent, because, as mentioned above, the value of v_k was used in updating $\hat{x}_k^+$ (See Eq. (19)). Therefore, considering this fact, our suggestion to calculate the variance of IS is presented as follows. These formulas are not derived using mathematical equations; rather, extensive simulation tests have shown that these formulas can give us more accurate results. The main idea that helped the authors to reach the following formulation was this fact that the variance of the difference between two correlated signals is always smaller than the maximum of signal variances.

$$E[IS\ IS^T] = R_k - HP_k^+H^T \quad (38)$$

$$\widehat{R}_k = E[IS\ IS^T] + HP_k^+H^T \quad (39)$$

$$E[IS\ IS^T] = \mathrm{diag}[DVR] \quad (40)$$

$$DVR_i = \frac{1}{2M}\sum_{j=0}^{2M-1} IS_{i,k-j}IS_{i,k-j} \qquad i = 1,2,\cdots,m \quad (41)$$

III. Mathematical Model Of CSTR

An irreversible and exothermic reaction A→B takes place inside the jacket CSTR that is shown in Figure 2 [16]. The reaction is operated by two proportional controllers that are used to regulate the outlet temperature and the tank level. A cooling jacket surrounds the reactor and the coolant is water in this case. Negligible heat losses, constant densities, perfect mixing inside the tank and uniform temperature in the jacket are assumed.

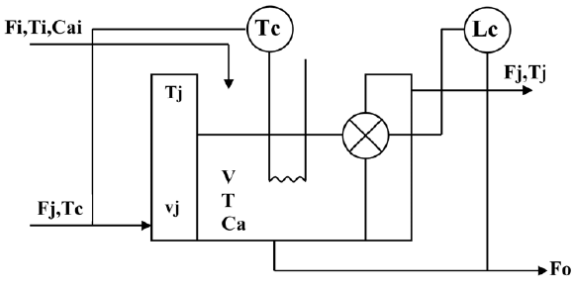

Fig.2.Schematic diagram of the process

The dynamic equations describing the system are given by [17]:

$$\frac{dV}{dt} = F_i - F_o \tag{42}$$

$$\frac{d(VC_a)}{dt} = F_i C_{ai} - F_o C_a - V\left(k_0 e^{-\frac{E_a}{RT}}\right) C_a \tag{43}$$

$$\rho c_p \frac{d(VT)}{dt} = \rho c_p (F_i T_i - F_o T) - \Delta HV\left(k_0 e^{-\frac{E_a}{RT}}\right) C_a - \\ -Ua_0(T - T_j) \tag{44}$$

$$\rho_j V_j c_j \frac{dT_j}{dt} = \rho_j c_j F_j (T_c - T_j) + Ua_0(T - T_j \tag{45}$$

$$F_o = 40 - 10(48 - V) \quad \text{(Level controller)} \tag{46}$$

$$\mathrm{F_j} = 49.9 - 4(600 - \mathrm{T}) \quad \text{(Temperature controller)} \tag{47}$$

Table 1 gives values of process parameters and steady state conditions:

Table 1: Non isothermal CSTR parameter

Notation	Variable	Steady state values
F_o	Outlet flow rate	40 ft^3/h
Ca_i	Inlet reactant concentration	0.5 lb. mol of A/ft^3
T	Reactor temperature	600°R
F_j	Coolant flow rate	49.9 ft^3/h
V	Volume of reactor	48 ft^3
Ca	Reactant concentration in reactor	0.245 lb.mol of A/ft^3
T_j	Jacket temperature	594.6°R
T_i	Inlet feed temperature	530°R
Notation	**Variable**	**Parameter values**
V_j	Volume of jacket	3.85 ft^3
E_a	Activation energy	30000Btu/lb.mol
U	Heat-transfer coefficient	150 Btu/h ft^2 °R
T_c	Inlet feed temperature	530°R
c_p	Heat capacity (process side)	0.75 Btu/lbm°R
ρ	Density of process mixture	50 lbm/ft^3
k_0	Frequency factor	$7.08\times1010h^{-1}$
R	Universal gas constant	1.99Btu/lb.mol°R
a_0	Heat-transfer area	250 ft^2
ΔH	Heat of reaction	-30000 Btu/lb.mol
C_j	Heat capacity (coolant side)	1.0 Btu/lbm°R
ρ_j	Density of coolant	62.3lbm/ft^3

IV. Simulation Study

For computer simulation, the CSTR nonlinear model is implemented using s-function and SIMIULINK facilities in MATLAB. The basic time unit is hours (hr) and the sampling time is taken to be equal to 0.005 hr.

As it is clear from Fig.2, the outputs of the system are volume and temperature of product, concentration of A, and temperature of CSTR jacket. For the simulation studies, measurements (V, T) have been assumed as the observed values in order to estimate all states of the system (V, T, C_a, T_j).

Proposed methodologies have been implemented on the CSTR plant. Figures 3-6 show the estimation of 4 states of the CSTR by 3 methods .The real value of standard deviation of measurement and process noises are 0.005 and 0.01 times of initial real states, respectively. Standard UKF is presented as the comparison criterion in which the correct noise variances are applied. In order to demonstrate the effect of fading and novel adaptive methods in the case of which process and measurement noises are not really known, incorrect values of noises covariance are introduced to these methods to examine their capability to extract the real values. The ratios of the incorrect values to the correct ones are 0.1 and 10, respectively, for R and Q in Figs. 3-6. These methods should compensate the effect of shortage in this information.

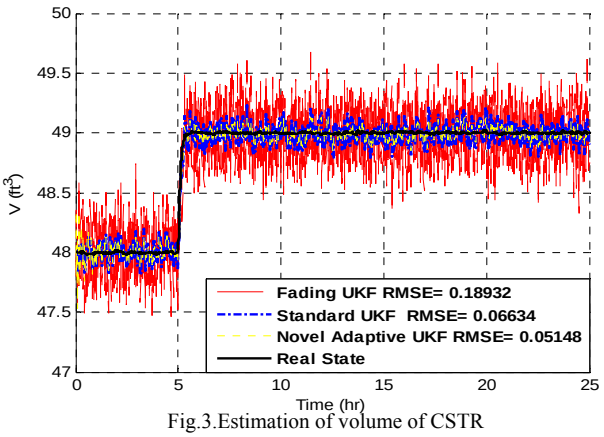

Fig.3.Estimation of volume of CSTR

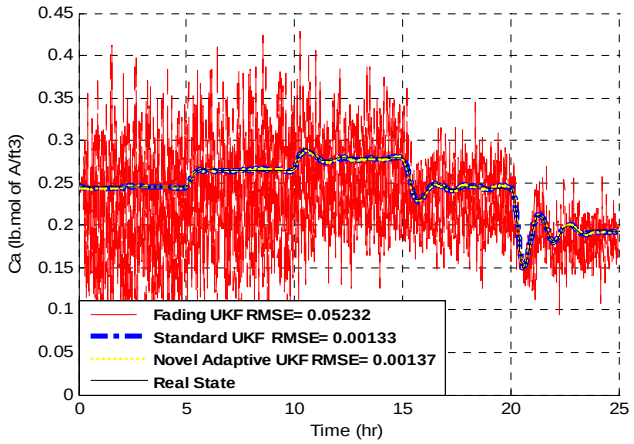

Fig.4.Estimation of product concentration

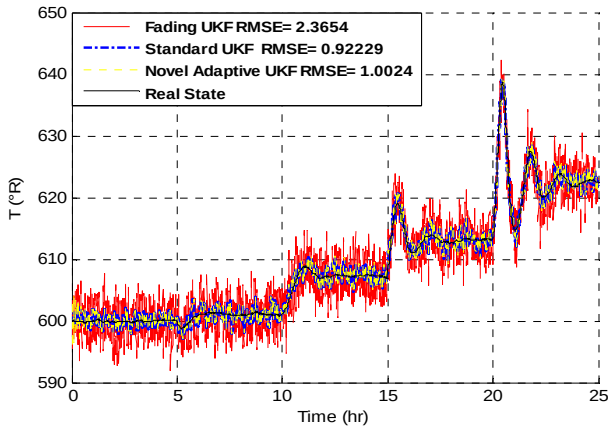

Fig.5.Estimation of Temperature of CSTR

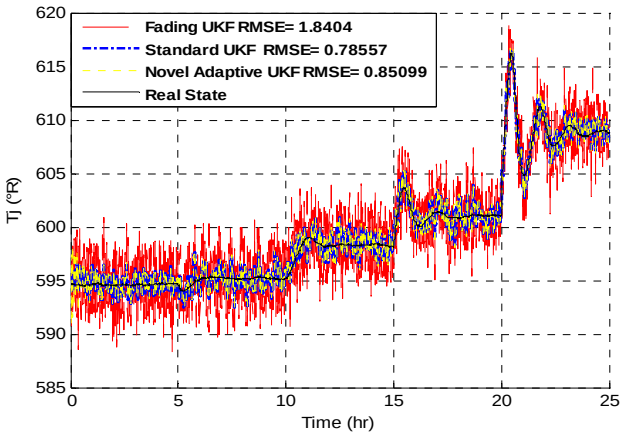

Fig. 6.Temperature Estimation of Jacket

Table 2 : Volume estimation error in terms of RMSE. The first row shows the ratios of incorrect values to correct values of noise variances. The incorrect values are just applied to fading and novel adaptive methods where Standard method use the actual value of noise and process variances.

Method \ R Q	1 0.1	0.1 1	10 0.1	0.1 10	0.1 0.1	10 10	10 0.01	0.01 10	0.1 0.01	0.01 0.1	0.1 100	100 0.01
Fading	0.08176	0.12283	0.15749	0.18932	0.14043	0.17986	0.19698	0.23296	0.16328	0.2138	0.23296	0.25694
Standard	0.06634	0.06634	0.06634	0.06634	0.06634	0.06634	0.06634	0.06634	0.06634	0.06634	0.06634	0.06634
Novel Adaptive	0.04494	0.04887	0.04481	0.05148	0.04667	0.04764	0.0439	0.05342	0.04488	0.04893	0.05342	0.04484

Table 3 : Concentration estimation error in terms of RMSE. The first row shows the ratios of incorrect values to correct values of noise variances. The incorrect values are just applied to fading and novel adaptive methods where Standard method use the actual value of noise and process variances.

Method \ R Q	1 0.1	0.1 1	10 0.1	0.1 10	0.1 0.1	10 10	10 0.01	0.01 10	0.1 0.01	0.01 0.1	0.1 100	100 0.01
Fading	0.01266	0.02814	0.01693	0.05232	0.0166	0.02472	0.01675	0.08526	0.01291	0.02854	0.08711	0.09699
Standard	0.00133	0.00133	0.00133	0.00133	0.00133	0.00133	0.00133	0.00133	0.00133	0.00133	0.00133	0.00133
Novel Adaptive	0.00133	0.00136	0.00132	0.00137	0.00144	0.00137	0.00131	0.00147	0.00152	0.00191	0.00139	0.00132

Table 4 : Temperature estimation error in terms of RMSE. The first row shows the ratios of incorrect values to correct values of noise variances. The incorrect values are just applied to fading and novel adaptive methods where Standard method use the actual value of noise and process variances.

Method \ R Q	1 0.1	0.1 1	10 0.1	0.1 10	0.1 0.1	10 10	10 0.01	0.01 10	0.1 0.01	0.01 0.1	0.1 100	100 0.01
Fading	1.1897	1.6812	1.1675	2.3654	1.31	1.3008	1.1653	2.8791	1.1985	1.6923	2.8789	1.1659
Standard	0.92229	0.92229	0.92229	0.92229	0.92229	0.92229	0.92229	0.92229	0.92229	0.92229	0.92229	0.92229
Novel Adaptive	0.97991	0.98933	0.98093	1.0024	0.98161	0.98445	0.98088	1.0111	0.98067	0.99102	1.0107	0.98122

Table 5 : Temperature of CSTR jacket estimation error in terms of RMSE. The first row shows the ratios of incorrect values to correct values of noise variances. The incorrect values are just applied to fading and novel adaptive methods where Standard method use the actual value of noise and process variances.

Method \ R Q	1 0.1	0.1 1	10 0.1	0.1 10	0.1 0.1	10 10	10 0.01	0.01 10	0.1 0.01	0.01 0.1	0.1 100	100 0.01
Fading	0.97449	1.3358	0.95735	1.8404	1.0634	1.0556	0.95575	2.2386	0.98122	1.3446	2.24	0.94913
Standard	0.78557	0.78557	0.78557	0.78557	0.78557	0.78557	0.78557	0.78557	0.78557	0.78557	0.78557	0.78557
Novel Adaptive	0.83008	0.83904	0.83104	0.85099	0.83172	0.83451	0.83095	0.85845	0.83075	0.84039	0.85794	0.83131

It should be mentioned that estimation of concentration state is the most important parameter in output quality of CSTR. However, the simulation of others outputs also verify the capability of the proposed method.

Tables 2-5 can clearly show that the proposed Novel Adaptive method is the best choice for industrial cases in which the real values of noise variances are unknown.

V. Conclusion

In this paper, we have studied the estimation procedure using Kalman filter theory. For highly nonlinear plants, as it is reported in the literature, the unscented Kalman filter is more accurate than extended Kalman filter, thus, UKF has been applied here to estimate states of a nonlinear CSTR plant. In order to reduce the error in estimations in which the noise variances are not known, Fading and novel adaptive methods of UKF has been presented in this paper. In novel adaptive method, variance matrices for both process and measurement noise signals were assumed unknown *a priori* and thus incrementally estimated and updated using a *sliding time window* paradigm within which an estimation of the noise variance is calculated and adaptively updated each time the window is shifted forward. The simulation results show the capability of the proposed novel adaptive method in performance monitoring of this nonlinear case study.

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