Detection of Soft Sensor Fault Using EKF Algorithm for Two Tank Interacting System

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Abstract. This paper deals with the identification of fault acting in the highly non-linear two-tank interacting system. This two-tank interacting system is reported with a sensor fault that is acting on the system which makes the system to be highly unstable. For detecting the fault, the estimation algorithm is used. Here the Extended Kalman Filter algorithm is used for identifying the sensor fault acting in the system. In the EKF algorithm residual is generated that indicates the presence of the fault. The residual that is generated gives the difference between the actual and the predicted measurement. This residual generation shows the magnitude of fault that is present in the system and also the nature of the fault that is acting in the system. This EKF based detection of fault indicates the occurrence of fault at the instant of time.

Keywords: State Estimation, Residual Generation, Two Tank Interacting System, Extended Kalman Filter, Fault Identification, Additive Fault.

1. Introduction

Nonlinear, dynamic structures are nowadays all over in our lives. They're in the Computers, ships, planes, and vehicles. Composite structures, such as chemical reactors, reactors in nuclear power plants and fractionating columns, are used in every industry. They work consistently, creating our lives more secure and more fun before these systems malfunction. Faults in complex structures are occurrences which rarely occur in unpredicted situations. The fault is a change in the characteristics property of the system. In dynamic systems, it is difficult to anticipate and avoid faults. Faults can cause accidents that lead to damages to human and huge economic loss.

A number of examples are: the explosion of nuclear power plant Chernobyl in Ukraine on 26 April 1986. It is not possible to eliminate the occurrence of faults in complex systems, to avoid the effects of faults, or at least to mitigate their severity. In order to minimize the occurrence of accidents, the most important step is to introduce fault detection and diagnosis method.

Model-oriented identification of faults in dynamic systems has gained much recognition over the past decades in the form of research and real-world technology studies. The problem in model-oriented fault detection and diagnosis concerns the consistency of the model that defines the monitoring system's behavior. The model-based FDD involves the detection and diagnosis of fault on a system by using methods that derive characteristics from available signals (i.e. known inputs and measurements) and mathematical model processes. Fault are identified by generating the residual that...
shows the difference between the actual and the predicted state measurements. A number of residuals can be generated, based on the individual faults that occur at different system locations. The examination of each residual leads to fault diagnosis until the threshold is surpassed. For non-linear systems, a large range of model-oriented FDD approaches, e.g., based on observer approach, parity space approach, and system recognition method. Here for this system, the Extended Kalman Filter algorithm is considered for identification of a fault.

![Model Based Residual Generation](image)

**Figure 1. Model Based Residual Generation.**

Here the model that is considered is two-tank system which is highly non-linear. The two-tank interacting system has the valve that is connecting between the two tanks and hence if any of the operating parameters get changed, this automatically changes the dynamics of the second tank or vice versa. Here in this system, the height of the tanks has to be held at a constant level say 4m and 3m respectively. Here the fault is introduced to the system as the additive representation of fault. The additive fault is widely used to represent sensor, actuator and component fault in the system. Just in state-space representation of the process, the additive sensor fault is added. The residual generation block produces the residual signal by comparing the system's input and output. The output produced will be, under no fault condition usually zero or close to zero. The method used to measure residuals is called generation of residuals. In order to remove fault symptoms from the system, such a technique is used, with the fault symptom reflecting the residual signal. The process of managing multiple faults lies in the simultaneous occurrence of similar fault effects generated by single faults. For correct residual evaluation, it is therefore necessary to gain the right residual structure. The residual assessment stage tests residuals for the faults and then uses a decision rule-base to decide where there were some faults. Which is shown in Figure 1 and this produces the residual vectors which is given in the equation below,

\[ r = y - \hat{y} \]  \hspace{1cm} (I)

Residuals may also be produced by methods of identification of changes, as noise, fluctuations and other unknown signals, calculated and measurable signals and other unknown signals are present.

Many scholars have studied sensor fault tolerant problem. In the following, we will analyse the contribution of some of these papers.

In [1] the author explains about the detection and isolation of fault by using fuzzy logic system and state estimation algorithm. The 20% sensor fault is added to the two tank systems. The detection of fault is implemented by using both the techniques and the performance is validated based on the effectiveness of fault detection.
This paper [2] demonstrates estimation of state by using EKF algorithm and also controlling the two tank system by using model predictive controller. The MPC controller strategy focused on basic use of some kind of system model to predict the variable governed over the horizon of finite time. From this paper, the internal state estimation of the system is learned and also the detection of systems sensor fault.

This paper [3] shows the detection, isolation and compensation of fault in three tank interacting system. Here the results shows the PI controller output with faults and the fault-tolerant output of the system. The adaptive observer whose function is to approximate both the undetermined performance and the inaccessible state variable for the calculation can be used to extend the work.

In [4] explains the fault tolerant control system. Here the first method is to estimate the fault by using LPV observer. Second method is to detect the fault by using fault decision scheme and to compensate the effect of fault is the third method.

In [5], the detection and fault tolerant control system of two tank is implemented by using observer based method and its performance is evaluated to check for its effectivness in detecting and isolating sensor fault in two tank system.

The work by Marta Capiluppi, Andrea Paoli [6] deals with the implementation of fault-tolerant control strategy for two-tank system. Here the FTC allows the permissible amount of fault in the system and thus making the system stable. Here the detection of sensor fault is learned.

2. Process description

The two interacting tank device is shown in Figure 2 consists of two tanks which are interacting in nature that is connected with the help of cross section valve. In the process the nonlinearity is introduced by the valves. The flow rate of tanks are $Q_{in1}$ and $Q_{in2}$ are defined as inputs for the dynamic model, whereas the two quantities $L_1(t)$ and $L_2(t)$ i.e. the fluid height in the tank is considered as outputs. The following differential equations are defined in 1 and 2.

For Tank 1,
$$S_1 \frac{dL_1}{dt} = Q_{in1} - c_1\sqrt{L_1 - L_2} \tag{2}$$

For Tank 2,
$$S_2 \frac{dL_2}{dt} = Q_{in2} + c_1\sqrt{L_1 - L_2} - b_2\sqrt{L_2} \tag{3}$$

Here the valve coefficient of the tank1 and tank are $c_1 = m_1n_1\sqrt{2\bar{H}}$ and $c_2 = m_2n_2\sqrt{2\bar{H}}$. The system parameter for two tank is given in Table 1.

![Figure 2. Two Tank Interacting System](image-url)
Table 1. System Parameter for Two Tank System

| SYSTEM PARAMETER                  | NOTATIONS |
|-----------------------------------|-----------|
| Tank1 and Tank2 area              | $S_1, S_2$|
| Gravity-induced acceleration      | $h$       |
| Maximum tank height               | $L_{\text{max}}$ |
| Cross section area of linking pipes | $m$   |
| Co-efficient of connecting pipes  | $n$       |
| Height of the tanks               | $L_1, L_2$ |

3. State estimation algorithm

State Estimation is a method to determine the state of a system by extracting measurement data from inaccuracies and errors.

3.1. Extended kalman filter

The most commonly used nonlinear state estimation technique employed in recent decades. Such methods require The term “higher order” is more than a direct linearization of the nonlinear system. These techniques include second order kalman filtering, iterated kalman filtering, sum-based kalman filtering, and grid-based kalman filtering. These filters have ways of reducing the inherent linearisation faults. Typically, they have better predicted performance. They do so at the risk of higher complexity and computational costs than the EKF.

The simple agenda of the EKF comprises state estimation of a discrete-time non-linear dynamics systems, defined as

$$C_k = U(c_{k-1}, f_k, e_k)$$

Where,

- $C_k$ indicates the estimation of state at the step $k - 1$.
- $f_k$ indicates the input vector, and
- $e_k$ indicates the noise in the process. The normal multivariate distribution with covariance is assumed to be drawn from the zero mean $Q_k$.

$$e_k = M(0, I_k)$$

At time, an observation (or measurement) $b_k$ of the true state $c_k$ is made accordingly as,

$$b_k = s(c_k, m_k)$$

Where,

- $c_{k-1}$ indicates the estimation of state at timestep $k$, and
\( m_k \) indicates the measuring noise known as Gaussian white sound with zero mean and covariance \( R_k \).

\[
m_k = M(0, I_k)
\]

(7)

The function \( u \) and \( s \) describes an \( n \)-dimension vector function and they are presumed to be identified. The function \( u \) is used to measure the approximate state from the previous data like the function \( s \) is used to calculate the estimated measurement from the previous predicted state. Every time the jacobian matrix is estimated and in extended kalman filter these matrices are used. This procedure is most important for linearising the non-linear state.

EKF consist of two phases: predicting and updating. The predicted phase uses the state estimate of the preceding the step time to make the state estimate at the current time step. Measurement at the same time is used for updating phase to refine this prediction in order to attain a better accuracy in the estimation of the state, for the same current phase time.

3.2. Extended kalman filter algorithm

3.2.1. Prediction state and covariance equation

Estimation of State

\[
\hat{c}_{k|k-1} = u(\hat{c}_{k-1|k-1}, e_k, 0)
\]

(8)

Estimation of Covariance

\[
K_{k|k-1} = U_kK_{k|k-1}U_k^T + J_k
\]

(9)

Here the following Jacobians describe the State transition matrices:

\[
U_k = \frac{\partial \hat{c}_k}{\partial c} | c_{k|k-1}, f_k
\]

(10)

3.2.2. Correction state and covariance equation

Residual measurement

\[
\tilde{b}_k = A_k - s(\hat{c}_{k|k-1}, 0)
\]

(11)

Covariance measurement

\[
H_k = S_kK_{k|k-1} + I_k
\]

(12)

Kalman gain

\[
P = K_{k|k-1}S_k^T + H_k^{-1}
\]

(13)

Estimation of State

\[
\hat{c}_k = \hat{c}_{k|k-1} + P_k\tilde{b}_k
\]

(14)

Estimation of Covariance

\[
K_{k|k} = (R - P_kS)K_{k|k-1}
\]

(15)

Here, the following Jacobians describe the measurement matrices:

\[
S_k = \frac{\partial s}{\partial c} | \hat{c}_{k|k-1}
\]

(16)
4. Simulation results

4.1. Identification of fault using EKF

Fig 3. Tank 1 Residual Plot

From the Fig 3, it is observed that the residual is generated which indicates the fault in the system. Here at time $t=50$ sec, $10\%$ sensor fault that is added to the system is shown through residual generation. This magnitude change indicates the percentage of fault that is added to the tank1.

Fig 4. Tank 2 Residual Plot

From the Fig 4, it is observed that the residual is generated which indicates the fault in the system. Here at time $t=50$ sec, $10\%$ sensor fault that is added to the system is shown through residual generation. This magnitude change indicates the percentage of fault that is added to the tank2.

5. Conclusion

In this paper, the identification of sensor fault in two tank interacting system has been implemented by using Extended Kalman Filter algorithm. The study on EKF algorithm has been made and the simulation results show that the algorithm is successful in identifying the sensor fault that occurs in both tank1 and tank2 for the detection of faults.
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