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Sliding Mode Observer Based Predictive Fault Diagnosis of a Steer-By-Wire System

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Abstract: This paper presents a nonlinear observer and prediction based analytical redundancy for a Steer-By-Wire (SBW) system. A Sliding Mode Observer was designed to estimate the vehicle steering angle by using the combined linear vehicle model, SBW system, and the yaw rate feedback. The estimated steering angle along with the current input was used to predict the steering angle at various prediction horizons via a long range prediction method. This analytical redundancy methodology was utilized to reduce the total number of redundant road-wheel angle (RWA) sensors, while maintaining a high level of reliability. The Fault Diagnosis algorithm was developed using a majority voting scheme, which was then used to detect faulty sensor(s) in order to maintain safe drivability. The proposed observer-prediction based fault detection algorithms as well as the linearized vehicle model were modelled in MATLAB-SIMULINK. Two different fault types were used to evaluate the effectiveness of the proposed algorithms: persistent and incipient faults. Simulation results show that the faulty sensor identification time decreases with the increase of prediction horizon illustrating advantages of the predictive analytical redundancy based algorithms against single point faults.

1. INTRODUCTION

The concept vehicles with SBW systems have demonstrated numerous benefits (Shibahata [2005]). However, the overall cost of highly reliable SBW system is still several times higher than the conventional steering systems, primarily due to the presence of multitude of redundant components (sensors, microcontrollers, actuators etc.). Model-based fault detection techniques can eliminate the need for redundant sensors in SBW vehicles, lowering the cost without compromising the reliability.

There are a number of important steering functional requirements for a Steer-By-Wire system, namely, (i) directional control and wheel synchronization, (ii) adjustable variable steering feel, (iii) adjustable steering wheel returns capability, (iv) variable end of travel stop for steering wheel, (v) variable steering ratio, etc.

The concept of analytical redundancy has been investigated in the context of aerospace applications, primarily utilizing Eigen-structure theory (Patton et al [1986]). However, most of these articles were aimed at isolated subsystems in an aircraft or a spacecraft (Venkateswaran et al [2002], Zolghadri et al [1998], Suzuki et al [1999], Dong et al [1996], Kelly [1996]). Fly-By-Wire (FBW) systems are mostly based on full hardware redundancies. As a result, analytical redundancy methodologies have not been utilized to a great extent in FBW systems. Introduction of Drive-By-Wire (DBW) technology is more challenging in the automobile market, mainly because automobile consumers cannot afford the high cost of redundant systems the aerospace industry can. Each extra sensor, actuator, and Electronic Control Unit (ECU) increases the overall cost and weight of the vehicle. With the profit margin already low, this approach will not be acceptable to the automobile industries. By employing analytical redundancy techniques instead of hardware redundancy, it will be possible to bring the overall cost of such system down to a point that will be attractive to the automakers for mass production without sacrificing the high level of safety and reliability required by the consumers. Through analytical redundancy, the vehicle steering angle can be estimated from the states measured by other sensors without using an extra steering position sensor.

In this research, the analytical redundancy based fast fault detection algorithms was developed that based on physical models, nonlinear estimator and generalized predictive algorithms. In this algorithm, outputs from the a number of redundant sensors as well as analytical sensor are checked against each other for a number of times before declaring a component to be faulty. The analytical sensor output is the combination exertion of the full vehicle model, nonlinear Sliding Mode Observer, and the ling range prediction algorithm. The yaw rate signal can be measured with inexpensive sensors. Therefore with the measured yaw rate and the measured motor current input, the road wheel steering angles are estimated with the Sliding Mode Observer. Thereafter the steering angles were predicted by a long range predictor at variable prediction horizons with the participation of estimated steer angle and the motor current.

The proposed research concept is utilizes the long range prediction based fault detection, based on the analytical model of the SBW system (Figure 1) which would provide added safety to the SBW system via fast and robust fault detection and isolation of a component failure in such a system.

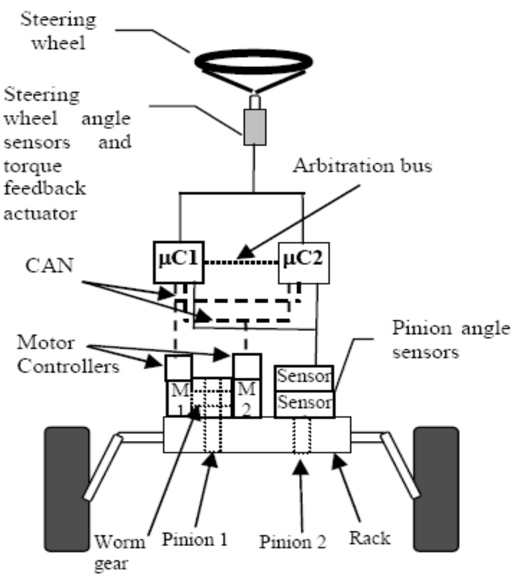

Fig. 1 Electronic architecture of an SBW system.

Since analytical redundancy methods are model-based, long-range prediction based Fault Detection, Isolation, and Accommodation (FDIA) algorithms is appropriate in such an application since modeling errors are inevitable in real-world systems. Furthermore, long-range prediction based FDIA methods (Figure 2) provide robustness against external disturbances which are expected in a DBW vehicle having a multitude of electric and electronics components. The fundamental concept in this proposition is that the sensor outputs are compared against the analytical counterpart (analytical redundancy) whose outputs are predicted several time step ahead via generalized predictive algorithm. In the event of a component failure, the predicted output will deviate from the sensor outputs several time steps ahead, thus reducing the detection latency.

2. OBSERVER AND PREDICTOR BASED MODELING

An observer can be designed by combining the steering system model and vehicle model (Anwar and Chen [2006]):

$$\dot{x} = Ax + Bi_m + E\tau_f$$

$$x = \begin{bmatrix} \beta & r & \theta & \dot{\theta} \end{bmatrix}^T$$

$$A = \begin{bmatrix} \frac{-C_{\alpha,f} - C_{\alpha,r}}{mV} & -1 + \frac{C_{\alpha,r}b - C_{\alpha,f}a}{mV^2} & \frac{C_{\alpha,f}}{mV} & 0 \\ \frac{C_{\alpha,r}b - C_{\alpha,f}a}{I_z} & \frac{-C_{\alpha,f}a^2 - C_{\alpha,r}b^2}{I_z V} & \frac{C_{\alpha,f}a}{I_z} & 0 \\ 0 & 0 & 0 & 1 \\ \frac{(t_p + t_m)C_{\alpha,f}}{J_w} & \frac{a(t_p + t_m)C_{\alpha,f}}{J_w V} & \frac{-(t_p + t_m)C_{\alpha,f}}{J_w} & \frac{-b_w}{J_w} \end{bmatrix}$$

$$B = \begin{bmatrix} 0 & 0 & 0 & \frac{k_m}{J_w} \end{bmatrix}^T ; E = \begin{bmatrix} 0 & 0 & 0 & -\frac{1}{J_w} \end{bmatrix}^T \qquad (1)$$

$$C = \begin{bmatrix} 0 & 0 & 1 & 0 \end{bmatrix}$$

The motor current is the input to the system and the torque due to Coulomb friction is treated as a disturbance. The above system is fully observable.

2.1 Sliding Mode Observer (SMO)

The motivations for using Sliding Mode Observer are, it is model free and robust respect to bounded uncertainty. It can work under much less conservative condition. The idea underlying SMO observer design methods can be illustrated for a linear time-invariant system (Utkin et al [1999]):

$$\dot{x} = Ax + Bu \qquad (2)$$

$$y = Cx \qquad (3)$$

$$y \in \Re^l, \; x \in \Re^n, \; rank(C) = l$$

The pair (C, A) is assumed to be observable and n is order of the system.

A linear asymptotic observer is designed in the same form as the original system (2) with an additional input depending on the mismatch between the real values (3) and the estimated values of the output vector:

$$\dot{\hat{x}} = A\hat{x} + Bu + L(y - C\hat{x}) \qquad (4)$$

where $\hat{x}$ is an estimate of the system state vector and $L \in \Re^{n \times l}$ is an input matrix. The state vector of the observer $\hat{x}$ is available since the auxiliary dynamic system is

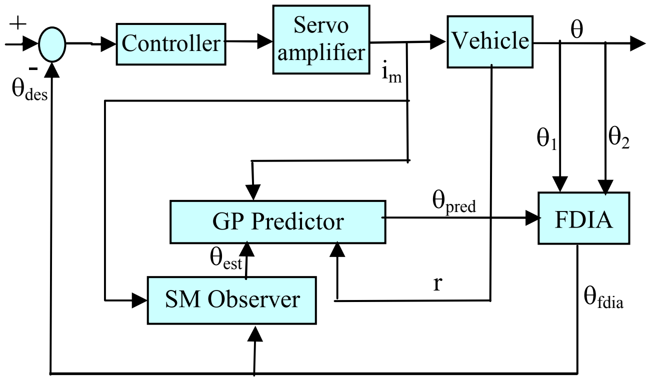

Fig. 2 Road wheel angle estimation and fault detection, isolation, and accommodation (FDIA).

implemented in a controller. The motion equation with respect to mismatch $\bar{x} = x - \hat{x}$ is of form:

$$\dot{\bar{x}} = (A + LC)\bar{x} \qquad (5)$$

The behavior of the mismatch governed by homogeneous Equation (5) is determined by eigenvalues of matrix (A+LC). For observable systems, they may be assigned arbitrarily by a proper choice of input matrix, L. It means that any desired rate of convergence of the mismatch to zero or estimate $\hat{x}(t)$ to state vector x(t) may be provided. Then any full-state control algorithms with vector $\hat{x}(t)$ are applicable.

The order of the observer may be reduced due to the fact that rank(C) = l and the observed vector may be represented as:

$$y = C_1 x_1 + C_2 x_p$$

$$x = \begin{bmatrix} x_1 & x_p \end{bmatrix}^T \qquad (6)$$

$$x_1 \in \Re^l, x_p \in \Re^{n-l}, \det(C_1) \neq 0$$

It is sufficient to design an observer only for vector x_p, then the components of vector x_1 are calculated as,

$$x_1 = C_1^{-1}(y - C_2 x_p) \tag{7}$$

Write the system Equations (2) and (3) in space (y,x_p) as,

$$\dot{y} = A_{11}y + A_{12}x_p + B_1 u$$
$$\dot{x}_p = A_{21}y + A_{22}x_p + B_2 u \tag{8}$$

where, $MAM^{-1} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}, MB = \begin{bmatrix} B_1 \\ B_2 \end{bmatrix}, M = \begin{bmatrix} C_1 & C_2 \\ 0 & I_{n-l} \end{bmatrix}$

The coordinate transformation M in nonsingular, $\det(M) \neq 0$. Therefore, applying the simple Sliding Mode Observer (SMO) in the state space system equation,

$$\dot{\hat{x}} = A\hat{x} + Bu + L\,\mathrm{sgn}(y - C\hat{x}) \tag{9}$$

where, $\mathrm{sgn}(z) = col(\mathrm{sgn}(z_1),...,\mathrm{sgn}(z_n))$

$$\mathrm{sgn}(z) = \begin{cases} +1 & if, z > 0 \\ -1 & if, z < 0 \end{cases}$$

Under a suitable choice of the gain matrix L in the observer, sliding occurs on the manifold $y - C\hat{x} = 0,$ and it becomes equivalent to the reduced order observer. The discontinuous vector function $v = L\,\mathrm{sgn}(y - \hat{y})$. Now from Equation (8),

$$\dot{\hat{y}} = A_{11}\hat{y} + A_{12}\hat{x}_p + B_1 u + L_1\,\mathrm{sgn}(y - \hat{y})$$
$$\dot{\hat{x}}_p = A_{21}\hat{y} + A_{22}\hat{x}_p + B_2 u + L_2\,\mathrm{sgn}(y - \hat{y}) \tag{10}$$

The system for the error $\bar{y} = y - \hat{y}$ is of the form,

$$\dot{\bar{y}} = A_{11}\bar{y} + A_{12}\bar{x}_p + B_1 u + L_1\,\mathrm{sgn}(\bar{y})$$
$$\dot{\bar{x}}_p = A_{21}\bar{y} + A_{22}\bar{x}_p + B_2 u + L_2\,\mathrm{sgn}(\bar{y}) \tag{11}$$

The vector function $v \in \Re^l$ is chosen such that sliding mode is enforced in the manifold $\bar{y} = 0$ and the mismatch between the output vector y and its estimate $\hat{y}$ reduced to zero. A vector L_2 must be found such that the mismatch $\bar{x}_p = x_p - \hat{x}_p$ between x_p and its estimate $\hat{x}_p$ decays as the desired rate. Equivalent value of the discontinuous function:

$$L_1\,\mathrm{sgn}(\bar{y}) = A_{12}\bar{x}_p \tag{12}$$

For simplicity, L_1 is considered as 1 and equation (12) becomes:

$$\mathrm{sgn}(\bar{y}) = A_{12}\bar{x}_p \tag{13}$$

Now the equation on the sliding manifold appears from equation (11):

$$\dot{\bar{x}}_p = (A_{22} - L_2 A_{12})\bar{x}_p \tag{14}$$

2.2 *Generalized Prediction Based Predictor*

A class of predictive self-tuning controllers, known as Generalized Predictive Controller (GPC) [Clarke et al (1987)], have shown robustness against unstable plants, non-minimum-phase plants, model overparameterization, and uncertain process dead time. These controllers have also been observed to provide offset free behavior for the closed loop system since they include an integral action. These set of controllers have been very successful in regulator or tracking type observer applications. In the context of long range prediction, the prediction horizon, *j* is a tunable design variable that can be set to any value according to the desired prediction range. The predictive nature of the GP (Generalized Prediction) based predictor algorithm comes from the use of the Diophantine equation. Through the use of Diophantine equation, the output of the plant is predicted *j-step* ahead of present time. This prediction output is then used for future fault detection and identification.

Considering the state space equations (2) and (3), a transfer function can be obtained as follows:

$$G(s) = \frac{U(s)}{Y(s)} = C(sI - A)^{-1}B \tag{15}$$

After discretization of the equation (15) a more general form of the dynamic model of the dynamic model of the vehicle model can be written as (Hasan [2007]):

$$A(z^{-1})Y(z) = B(z_{-1})U(z) \tag{16}$$

where $A(z^{-1})$ and $B(z^{-1})$ are polynomial of order na and nb respectively in the backward shift operator in time, z^{-1}. $A(z^{-1})$ and $B(z^{-1})$ have the following forms:

$$A(z^{-1}) = d_0 + d_1 z^{-1} + d_2 z^{-2} + \ldots + d_{na}z^{-na}$$
$$B(z^{-1}) = n_0 + n_1 z^{-1} + n_2 z^{-2} + \ldots + n_{nb}z^{-nb} \tag{17}$$

In order to make a prediction of the future output of the road wheel angle, the Diophantine identity is used to derive the j-step ahead prediction of $\Delta U(t+j)$.

$$1 = E_j(z^{-1})A(z^{-1}) + z^{-j}F_j(z^{-1}) \tag{18}$$

Where E_j and F_j are uniquely defined polynomials for a given $A(z^{-1})$ and the prediction interval *j*. In the present work, the recursive technique similar to that suggested by Clarke et al (1987) has been used to obtain E_j and F_j. This makes the procedure computationally very efficient. It has been shown that with increasing *j* only the highest order term in $E_{j+1}(z^{-1})$ changes while the rest of the coefficients remain the same in $E_j(z^{-1})$. Therefore, we can write:

$$E_{j+1}(z^{-1}) = E_j(z^{-1}) + e_j z^{-j} \tag{19}$$

where, $E_j(z^{-1}) = e_0 + e_1 z^{-1} + e_2 z^{-2} + ... + e_{j-1}z^{-(j-1)}$

In the degree of polynomial $A(z^{-1})$ is na, then the degree of $F_j(z^{-1})$ becomes na. The coefficients of the polynomial $F_j(z^{-1})$ may then be denoted as:

$$F_j(z^{-1}) = f_{j,0} + f_{j,1}z^{-1} + f_{j,2}z^{-2} + ... + f_{j,na}z^{-na} \tag{20}$$

2.3 *Steering Angle Prediction*

GP based prediction supposed to be executed for the discrete model. Hence the forth order vehicle model has been discretized (Ogata [1987]) to make itself compliant with the predictor. From the equations (16) – (17), the Diophantine prediction equation (*j-step* ahead predictor) is given by,

$$E_j(z^{-1})(d_0 + d_1 z^{-1} + d_2 z^{-2} + d_3 z^{-3} + d_4 z^{-4})\Delta + z^{-j}F_j(z^{-1}) = 1 \tag{21}$$

Multiplying equation (21) with θ(t+j) and rearranging that equation, we obtain:

$$\theta(t+j) = F_j(z^{-1})\theta(t) + E_j(z^{-1})(n_0 + n_1 z^{-1} + n_2 z^{-2} + n_2 z^{-3} + n_4 z^{-4})\Delta i_m(t-j+1) \quad (22)$$

$$where, \Delta = (1 - z^{-1})$$

Equation (22) predicts the value of the pinion angle θ in the future (*j* - time step ahead).

$$\theta(t+j) = F \times \theta(t) + EB \times \Delta i_m(t-j+1) \quad (23)$$

The matrices $F \in \Re^{N\times 5}$ and $EB \in \Re^{N\times(N+5)}$ are calculated by using the MATLAB script.

2.4 *Implementation of SM and GP Based Observer for Modified Vehicle Model*

To validate the Fault Detection, Isolation and Accommodation (FDIA) algorithm; the foremost justification was ensured as the SMO and GP-based predictor is a good fit for the proposed vehicle model. Therefore, the SMO and GP-based predictor were executed individually to confirm their workability.

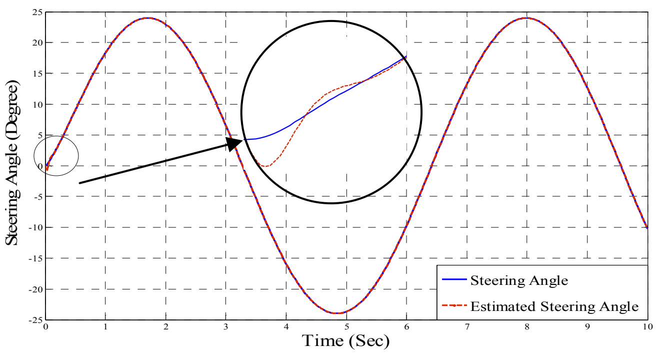

Fig. 3 Comparison of the actual steering angle with the estimated steering angle.

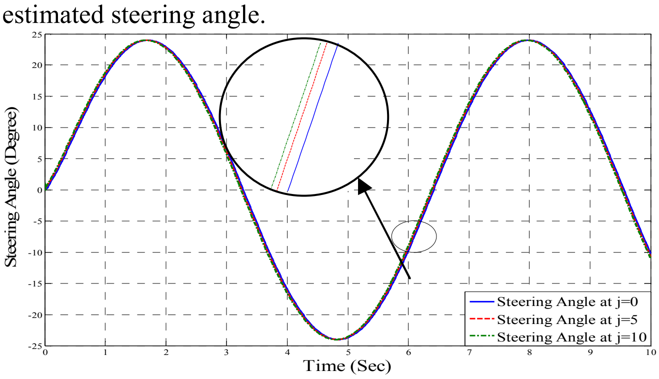

Fig. 4 GP Based Prediction of Steering Angle.

With the input of motor current and yaw rate sensor, the road wheel angle has been estimated and consequently substantiates its applicability. In Figure 3, the dotted line is showing the estimated steering angle follows the actual steering angle after a fraction of seconds.

In Figure 4, the GP based predictor has been implemented and shows that the steering angle can be predicted ahead of the instantaneous time. Higher the prediction horizon, faster the prediction of the steering angle.

Both simulation results show that the SMO and GP based predictor can be implemented into the modified vehicle model hence substantiate their performance.

3. SIMULATION RESULTS

3.1 *Initialization of Vehicle Model for Simulation*

In the full vehicle model, the parameter initialization (Anwar and Chen [2006]) is set as follows: F_w = 2 (N-m); J_w = 0.5 (kg-m^2); b_w = 20; k_m = 0.5; I = 3136 (kg-m^2); C_f = 18000 (N/rad); C_r = 47000 (N/rad); m = 1250 kg; V = 8 (m/s); a = 1.05 (m); b = 1.71 (m); $C_0 = (C_f + C_r)$ (N/rad); $C_1 = (bC_r - aC_f)$ (N-m/rad); $C_2 = (a^2C_f + b^2C_r)$ (N-m^2/rad); t_p = 0.0381 (m); t_m = 0.04572 (m); $C_3 = (t_p + t_m)C_f$ (N-m/rad); K = 80; T = 0.005 (sec).

The vehicle model presented in this thesis is evaluated on a validated SIMULINK model (Anwar and Chen [2006]). The cornering coefficients has been considered for a light weight passenger FWD car. Therefore the mass and dimensions of the vehicle were perceptibly standard for the small passenger car. The simulation process has been appraised for a slow moving vehicle and the pneumatic and mechanical trails have been carried out from the standard passenger car tires specification. The driver's factor is chosen as nominal driving effect. But the sample time can be deviated according to the dynamic requirement of the system.

3.2 *Faults Types and Their Implications*

Two major faults usually introduced into a dynamic system can be named as –

i) Persistent or Permanent fault
ii) Incipient fault

The persistent fault type is illustrated in figure 5. Amplitude change fault can be either positive amplitude change or negative amplitude change types. Incipient fault should be handled at the early stage of the system operation otherwise according to their nature; they are gradually increased to a larger extent that could be difficult to control. The amplitude change type incipient faults are shown in figures 7, 9.

These two most available types fault are introduced into the vehicle model system and verified the FDIA methodology as well as provides the efficient proposition of SMO (Sliding Mode Observer) and GP based predictor for the SBW (Steer-By-Wire) system.

In order for the SBW system to be robust, the sensor measurements must be accurate and reliable. Therefore, any faulty signal must be eliminated to prevent undesirable steering effects. The Fault Detection, Isolation, and Accommodation algorithm (FDIA) (Anwar and Chen [2006]) used in this paper is able to handle single point fault without interrupting the functionality of the SBW system. This algorithm can be easily modified to handle multiple faults if more than three sensor signals are compared. The FDIA algorithm implemented in SIMULINK below is based on a majority voting scheme in which a minimum of three signals are required for this scheme to work. The sensor signals are compared against each other in real-time to determine the faulty signal where majority is assumed to be correct. This is based on the assumption that the event of a sensor failure is rare and the event of multiple simultaneous sensor failures is extremely rare. This algorithm can determine which sensor has failed by comparing its value against other sensors' values. This algorithm can manage hard-failures as well as soft-failures. Hard-failure is characterized by an abrupt or sudden sensor failure and soft-failure is characterized by biases or drifts in the signal over time. When a sensor fails, its signal is no longer used in the road wheel angle calculation. In such a situation the driver would be alerted of the sensor failure, but would also still be able to maintain safe control of the vehicle.

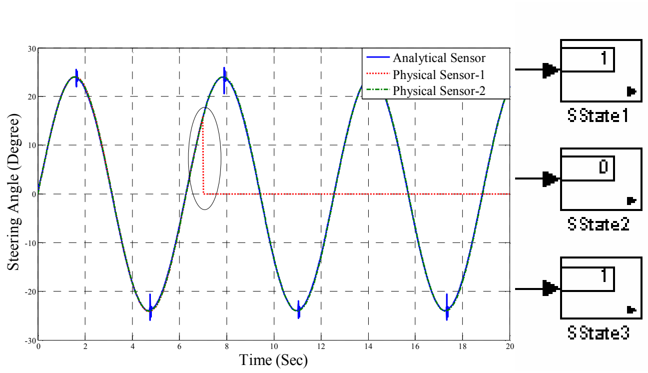

Fig. 5 Persistent zero sensor fault introduced in one of the two physical sensors with the fault state displayed on the right

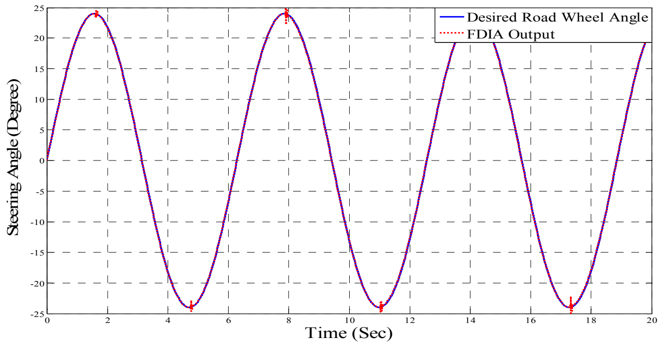

Fig. 6 FDIA output of sensor data after removing the persistent zero introduce fault in one physical sensor

A number of simulation runs were performed in order to evaluate the developed methodology of estimating and then predicting the road wheel angle to detect and control them. And some simulations were observed to verify the advantages of higher prediction horizon into the dynamic systems. The SBW controller, the yaw angle observer, the road wheel angle estimator, the FDIA algorithms, and the Generalized Predictive (GP) based predictor are combined with a simplified vehicle model with an SBW actuation system. The combined model was given a sinusoidal steering input. Fault was then injected to one of the three road wheel angle sensors whether one of them was analytical sensor. Fault flags and the output of the road wheel angle from the FDIA block are then recorded.

Persistent zero introduce fault was injected by making the sensor out a constant value. It was considered a faulty signal by the FDIA block and was eliminated from the FDIA block output. Figure 5 shows the FDIA block output with the removal of the fault from the system.

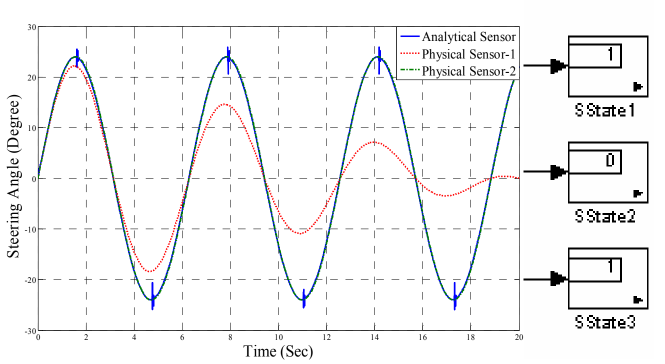

Fig. 7 Negative amplitude change type incipient fault introduced in one of the two physical sensors with the fault state displayed on the right

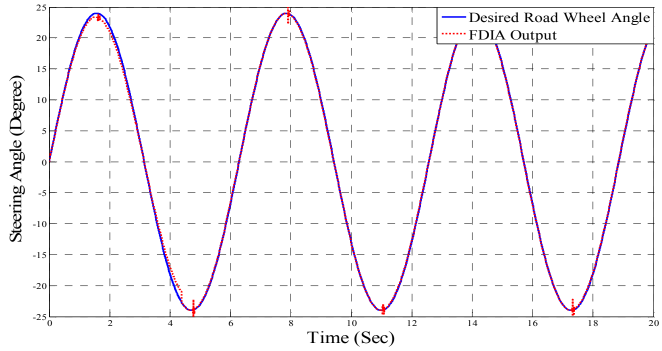

Fig. 8 FDIA output of sensor data after removing the negative amplitude change type incipient fault in one physical sensor

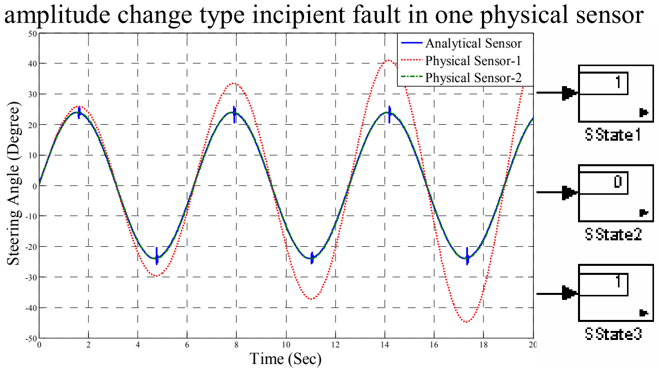

Fig. 9 Positive amplitude change type incipient fault introduced in one of the two physical sensors with the fault state displayed on the right

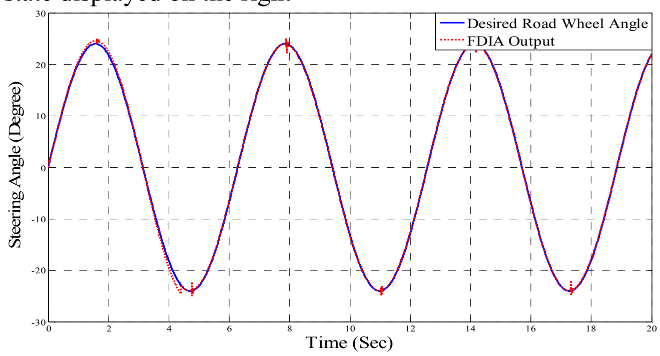

Fig. 10 FDIA output of sensor data after removing the positive amplitude change type incipient fault in one physical sensor

Figures 7 and 9 show the sensor signals of the amplitude change type incipient faults. These faults are introduced into the 2nd physical sensor though m-file. These three figures show the nature of incipient fault as gradual increment with time. According to the proposed estimated and predicted fault tolerant control methodology, these faulty signals were eliminated and the FDIA output signals (Figures 8 and 10) verify the efficiency of the GP based prediction.

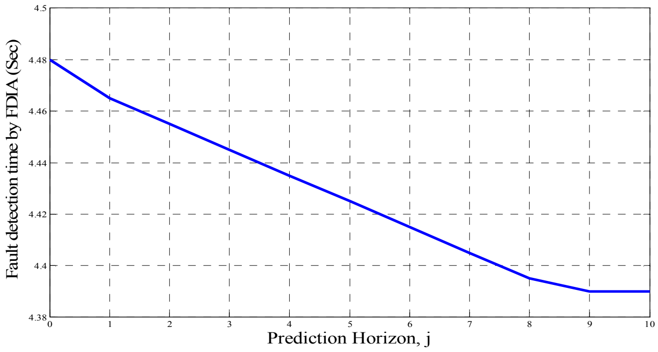

Fig. 11 Effect of prediction horizon for the amplitude change type incipient fault (lower magnitude) into the physical sensor

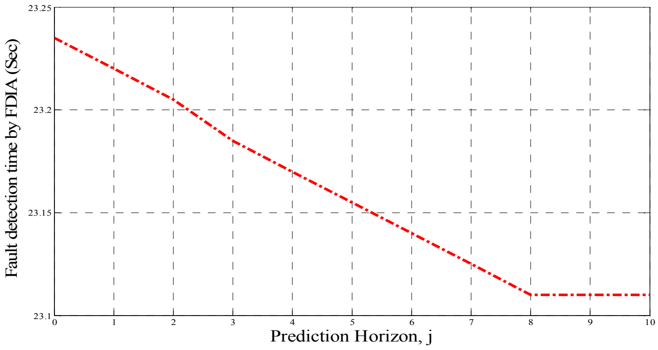

Fig. 12 Effect of prediction horizon for the amplitude change type incipient fault (higher magnitude) into the physical sensor

Now to show the effect of GP based prediction with the different prediction horizons; it's convenient to observer the effects with the incipient fault. Because by definition the incipient fault is gradually increases with time therefore the consequence of prediction horizon is more prominent. Figures 11 – 12 show the effect of prediction horizon for the various magnitudes of amplitude change type incipient fault.

Figures 11-12 illustrate that the fault detection time for incipient faults decreases significantly with increase in the prediction horizon, thereby improving the efficiency of fault detection.

4. CONCLUSIONS

This research work has demonstrated that it is possible to increase the level of robustness of a fault tolerant SBW system via successful implementation of Sliding Mode Observer (SMO) and Generalized Predictor (GP) based fault tolerant control. In the present work, a nonlinear Sliding Mode Observer (SMO) was designed and implemented to estimate the road wheel angle with available sensor output of yaw angle and motor input current. Through the proposed predictive analytical redundancy based fault detection and isolation algorithm, an extra level of redundancy was possible without any extra hardware. The proposed algorithms rendered the SBW system with a robust fault tolerant system as evidenced by the simulation results. It was also observed that the reliability of the proposed methodology increases with the increase of prediction horizon as it reduces the detection time for the faulty sensors.

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