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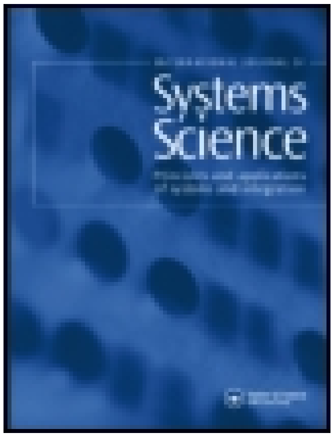

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Experimental application of nonlinear minimum variance estimation for fault detection systems

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The purpose of this paper is to present an experimental design and application of a novel model-based fault detection technique by using a nonlinear minimum variance (NMV) estimator. The NMV estimation technique is used to generate a residual signal which is then used to detect faults in the system. The main advantage of the approach is the simplicity of the nonlinear estimator theory and the straightforward structure of the resulting solution. The proposed method is implemented and validated experimentally on DC servo system. Experimental results demonstrate that the technique can produce acceptable performance in terms of fault detection and false alarm.

Keywords: fault detection and isolation; nonlinear systems; state estimation

1. Introduction

The need for high performance, efficiency, safety and reliability in modern engineering systems has focused interest in the *fault detection and isolation* (FDI) problem. A fault is defined as an unexpected change in a system with component malfunction or variation in operating condition. Some faults, if not promptly and properly detected, could turn into unrecoverable failures, causing serious damage and even loss of human lives (Alkaya & Eker, 2011).

In the literature, faults can be assumed to take place in different parts of a system and are classified as actuator faults or sensor faults (Isermann, 2006). Actuator faults can represent partial or complete loss of control action. A total actuator fault can occur as a result of a breakage, cut or burned wiring, short-circuit or the presence of foreign body in the actuator (Isermann, 2006). Sensor faults are incorrect outputs from the sensors. They can also be subdivided into partial and total faults.

Fault detection (FD) methods can be classified into two major categories; model-based and data-driven approaches (Venkatasubramanian, Rengaswamy, & Kavuri, 2003a). The model-based FDI approaches include parity space, parameter estimation and observer-based approaches. The observer-based FDI method is one of the most effective and has received significant interest from industry (Venkatasubramanian, Rengaswamy, & Kavuri, 2003b). Model-based approaches typically rely on two steps: residual generation; the procedure of extracting fault symptoms from the process, and residual evaluation; the procedure of decision-making (Chow & Willsky, 1984). The residuals are often generated using either an observer, for deterministic models, or an optimal filter for stochastic models.

Observer-based FD methods use measurements of the actual signals and estimates of the signals to generate the residual. The residual should be defined to become large when a fault occurs, to avoid false alarms (Hur, Katebi, & Taylor, 2011), but remain as small as possible due to other uncertainties such as unknown disturbances and modelling errors.

Residual generation approaches have been developed successfully for linear systems. However, much less work has been done for nonlinear systems. This is primarily due to the complexity of nonlinear systems. The area of FDI for nonlinear systems is not covered completely yet, so it is worthy of study (Alrowaie, Gopaluni, & Kwok, 2012).

There is some existing literature on the use of a nonlinear estimator for FDI. The most popular estimator for nonlinear processes is known to be *extended Kalman filter* (EKF) (Gerasimos, 2012). Although widely used, EKFs have some deficiencies, including the requirement of differentiability of the state dynamics as well as susceptibility to bias and divergence in the state estimates. The *unscented Kalman filter*, on the contrary, uses the nonlinear model directly instead of linearising it (Mirzaee & Salahshoor, 2012) and hence does not need to calculate the Jacobian and can achieve higher order accuracy. *Particle filters* or Sequential Monte Carlo methods are considered a general numerical tool to approximate the a-posteriori density in nonlinear and non-Gaussian filtering problems. The main

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drawback with the particle filter is that it is very demanding computationally (Shamsher, 2009).

In this study, the *nonlinear minimum variance* (NMV) estimator is implemented experimentally to DC servo system to generate a residual signal for fault detection applications. The novelty of this work lies in the design steps and the practical implementation of the NMV estimation-based fault detection technique .The strong point of this technique is that a general nonlinear operator is used to represent the nonlinearity of the channel or of the measurement sensor. This might involve a set of nonlinear equations or even include a look-up table or be a model obtained from a neural or fuzzy-neural network. The main advantages of the proposed estimator are that no online linearisation is required, as in the extended Kalman filter, and implementation is easy. The cost function to be minimised is the variance of the estimation error and a relatively simple optimisation procedure and solution results (Grimble, 2007).

The major contribution of the paper is to be the first real-time application of NMV estimator for fault detection problems, for either sensor or actuator faults. It is a fact that the estimation method takes account of signal channel paths that make the method so suitable for fault and condition monitoring systems.

The roadmap for this study is as follows. The derivation of NMV estimation method is given in Section 2. NMV-based residual generation for fault detection is described in Section 3. Experimental implementation and the results of the proposed fault detection method are illustrated in Section 4. Finally, the conclusions are summarised in Section 5.

2. Nonlinear minimum variance estimation

The theory of *nonlinear minimum variance estimation* (NMVE) was introduced by Grimble (2007) using polynomial system models (Grimble, 1995, 2006), and later state-equation-based models (Grimble, 2011, 2012). The NMVE technique involves the estimation of a signal that passes through a communications channel having nonlinearities and communication/transport delays (Grimble, 2006). The measurements are assumed to be corrupted by a noise signal, which is correlated with the signal to be estimated. Signal and noise models are assumed to be linear and time invariant. The NMV estimator derivation is based on the minimisation of the error variance criterion. Consider the system shown in Figure 1, which includes the nonlinear signal channel model and linear measurement noise and signal models.

The signal channel model includes the nonlinearities that may involve both linear and nonlinear dynamics. The signal channel dynamics with a delay can be expressed as

$$(\mathcal{W}_{\text{channel}}\, f)(t) = \left(\mathcal{W}_{c1}\, z^{-\Lambda_0} W_{c0} f\right)(t) \quad (1)$$

where $z^{-\Lambda_0}$ denotes a diagonal matrix of the k step delay elements in the signal paths and $\Lambda_0 = kI$. The parallel path dynamics shown in Figure 1, by a dotted line, can be expressed as

$$\mathcal{F}_c(z^{-1}) = \mathcal{F}_{c0}(z^{-1}) z^{-\Lambda_0} \quad (2)$$

This is a fictitious channel, added to provide design tuning options, that can be used to represent uncertainties in channel knowledge, which provides additional design freedom. The combined signal source and noise signal $f(t) \in R^r$ is given as

$$f(t) = y(t) + n(t) \quad (3)$$

Consider the nonlinear system for the optimal estimation problem illustrated in Figure 1. The input and noise-generating processes have an innovations signal model with white noise signal input:$\varepsilon(t) \in R^r$ and it may be assumed to be zero-mean with covariance matrix $\text{cov}[\varepsilon(t), \quad \varepsilon(\tau)] = I\delta_{t\tau}$, where $\delta_{t\tau}$ denotes the *Kronecker delta-function*. The signals shown in the closed-loop system model of Figure 1 may be listed as follows:

$$\text{Noise: } n(t) = W_n \varepsilon(t) \quad (4)$$

$$\text{Inputsignal: } y(t) = W_s \varepsilon(t) \quad (5)$$

$$\text{Channelinput: } f(t) = y(t) + n(t) \quad (6)$$

$$\text{Linear channel subsystem: } s_0(t) = (W_{c\,0}\, f)(t) \quad (7)$$

$$\text{Weighted channel interference: } n_c(t) = (\mathcal{F}_c \varepsilon)(t) \quad (8)$$

$$\text{Nonlinear channel subsystem: } s_c(t) = (\mathcal{W}_{c1}\, s_d)(t) \quad (9)$$

$$\begin{aligned}\text{Nonlinear channel input: } s_d(t) &= z^{-\Lambda_0} s_0(t) \\ &= s_0(t-k) \quad (10)\end{aligned}$$

$$\text{Observations signal: } z(t) = n_c(t) + s_c(t) \quad (11)$$

$$\begin{aligned}\text{Message signal to be estimated: } s(t) &= W_c\, y(t) \\ &= W_c\, W_s \varepsilon(t) \quad (12)\end{aligned}$$

$$\text{Weighted message signal: } s_q(t) = W_q W_c\, y(t) \quad (13)$$

$$\text{Estimation error signal: } \tilde{s}(t \mid t-\ell) = s(t) - \hat{s}(t \mid t-\ell) \quad (14)$$

where $\hat{s}(t \mid t-\ell)$ denotes the estimate of the signal $s(t)$ at time t, given observations $z(t)$ up to time $t-\ell$. Value of ℓ may be positive or negative according to the following conditions: $\ell = 0$, for estimation; $\ell > 0$, for prediction; and

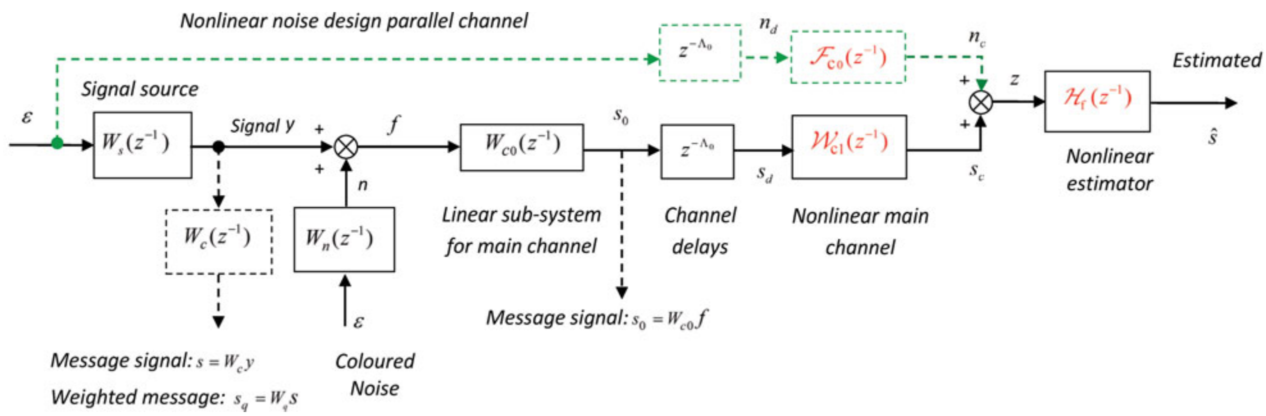

Figure 1. Signal and noise model and communication channel dynamics.

$\ell < 0$, for fixed-lag smoothing. The criterion for the nonlinear minimum variance estimator is given as follows:

$$J = \text{trace}\{E\{W_q\tilde{s}(t|t-\ell)(W_q\tilde{s}(t|t-\ell))^T\}\} \qquad (15)$$

where $E\{.\}$ denotes the expectation operator and W_q (Grimble, 2005) denotes a linear strictly minimum-phase dynamic cost-function weighting function matrix which is assumed to be strictly minimum phase, square and invertible.The estimate $\hat{s}(t \mid t-\ell)$ is assumed to be generated from a nonlinear estimator of the form:

$$\hat{s}(t \mid t-\ell) = H_f(t,\ z^{-1})z(t-\ell) \qquad (16)$$

where

$$\mathcal{H}_f(t, z^{-1}) = W_q^{-1} H_0 (\mathcal{F}_{c0} + \mathcal{W}_{c1}\ W_{c0}Y_f)^{-1} \qquad (17)$$

where $\mathcal{H}_f(t, z^{-1})$ denotes a minimal realisation of the optimal nonlinear estimator. Since an infinite-time ($t = -\infty$) problem is of interest, no initial condition term is required. The block diagram representation of $\mathcal{H}_f(t, z^{-1})$ will be as shown in Figure 2.

The terms H_0, A and Y_f used in Equation (18) can be calculated using the concept of power spectrum for the combined linear models using $\phi_{ff} = (W_s + W_n)(W_s^* + W_n^*)$,

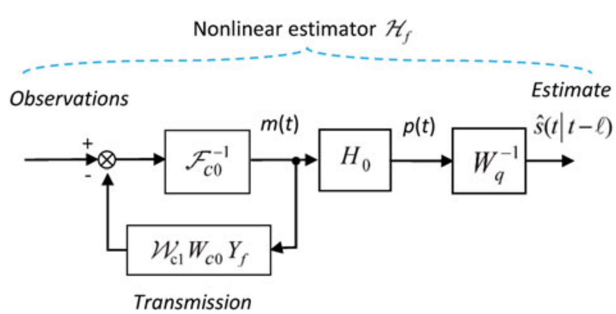

Figure 2. Implementation of the nonlinear estimator.

and where the notation for the adjoint of W_s implies $W_s^*(z^{-1}) = W_s^T(z)$, and in this case the z denotes z-domain complex number. The generalised spectral-factor Y_f may be computed using $Y_f Y_f^* = \phi_{ff}$, where $Y_f = A_0^{-1} D_{f0} = D_f A^{-1}$. The system models are assumed such that D_{f0} is strictly Schur polynomial matrix (Kucera, 1979, 1980) satisfying:

$$D_{f0} D_{f0}^* = (C_s + C_n)(C_s^* + C_n^*) \qquad (18)$$

The right-coprime polynomial matrix model can be defined as

$$\left[\, C_f \;\; D_f \,\right] A^{-1} = \left[\, W_q W_c W_s \quad Y_f \,\right] \qquad (19)$$

The polynomial operators H_0 now may be obtained from the minimal degree solution (H_0, F_0), with respect to F_0, of the following Diophantine equation:

$$F_0 A + G_0 z^{-k-\ell} = C_f \qquad (20)$$

The estimation error can be penalised in a particular frequency range by using a dynamic asymptotically stable weighting function $W_\Omega = A_\Omega^{-1} B_\Omega$, where A_Ω and B_Ω are polynomial matrices. The weighted error involves a linear path at the optimum. In the linear case, the modified cost function will have the following form (Parceval's theorem does not apply in the nonlinear case):

$$\begin{aligned} J &= \text{trace}\{E(W_\Omega e(t|t-\ell))(W_\Omega e(t|t-\ell))^T\} \\ &= \text{trace}\left\{1/(2\pi j) \oint_{z=1} (W_\Omega \Phi_{ee} W_\Omega^*) dz/z\right\} \end{aligned} \qquad (21)$$

3. NMVE-based fault detection

In NMVE, the nonlinearities are assumed to be in the signal channel or possibly in a noise channel representing the uncertainty. The simple solution that follows arises because

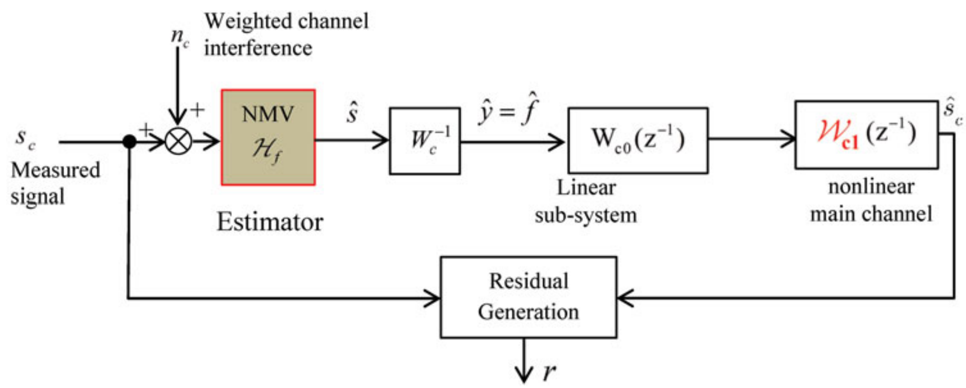

Figure 3. NMVE-based residual generation scheme.

of the assumptions of linearity for the signal-generating model and the results obtained here involve only a least-squares type of analysis (Grimble & Shamsher, 2010).

The fault detection techniques are often based on the generation of appropriate residual signals which have to be sensitive to faults themselves but independent of disturbances. *Model-based* FD methods are based on comparing the behaviour of the actual signal and an estimated signal of the system. Typically, it is shown that in the absence of a fault, the observer residual approaches zero. When a fault exists, this residual will be non-zero, and it may, therefore, serve as a fault indicator.

The block diagram of the proposed nonlinear minimum variance estimator, taking $\ell = 0$, based on residual generation for fault detection, is shown in Figure 3.

The residual signal can be generated by using measured signal $s_c(t)$and its estimate $\hat{s}_c(t)$, as

$$r(t) = s_c(t) - \hat{s}_c(t) \tag{22}$$

The NMV algorithm estimates the signal $\hat{s}$, so $\hat{s}_c$ might be defined in term of $\hat{s}$signal by using Equations (6), (7), (9) and (10) as follows:

$$\hat{y}(t) = W_c^{-1}\hat{s}(t) \tag{23}$$

$$\hat{f}(t) = \hat{y}(t) = W_c^{-1}\hat{s}(t) \tag{24}$$

$$\hat{s}_c(t) = \mathcal{W}_{c1}\, W_{c0}\hat{f}(t) \tag{25}$$

Then finally, the residual signal can be calculated substituting Equation (28) into Equation (23):

$$r(t) = s_c(t) - \mathcal{W}_{c1}\, W_{c0} W_c^{-1}\hat{s}(t) \tag{26}$$

This residual signal r is going to be checked with a reasonable threshold to detect that a fault has occurred in the system.

When there is a fault at the signal estimation point, the residual becomes

$$r(t) = s_c(t) - \mathcal{W}_{c1} W_{c0} W_c^{-1}\hat{s}(t) + \phi_f \tag{27}$$

$$= \mathcal{W}_{c1} W_{c0} W_c^{-1} s(t) - \mathcal{W}_{c1} W_{c0} W_c^{-1}\hat{s}(t) + \phi_f \tag{28}$$

If the plant is linear, this simplifies as

$$r(t) = W_{c1} W_{c0} W_c^{-1}\left(s(t) - \hat{s}(t)\right) + \phi_f \tag{29}$$

$$= W_{c1} W_{c0} W_c^{-1}\left(\tilde{s}(t\,|\,t)\right) + \phi_f \tag{30}$$

where ϕ_f is a fault and where $\phi_f \neq 0$ is the output arising from the signal fault. However, it can be only detected if term is large compared with estimation errors and the signal noise $\varepsilon(t)$.

3.1. *Threshold computation*

To achieve a successful fault detection based on the available residual signal, further effort is needed. Residual evaluation and threshold setting are used to distinguish the faults from the disturbances and uncertainties. A decision on the possible occurrence of a fault will then be made by means of a simple comparison between the residual feature and the threshold, as shown in Figure 4.

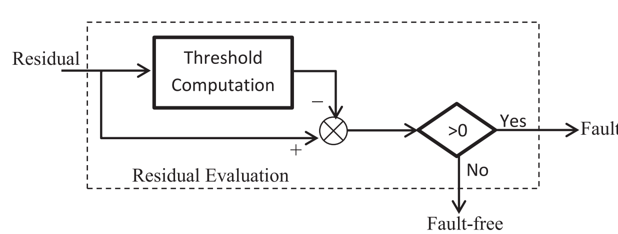

Figure 4. Residual evaluation.

In practice, the so-called limit monitoring and trend analysis are, due to their simplicity, widely used for the purpose of fault detection. For a given residual signal r, the limit monitoring may be expressed as follows:

$$\begin{array}{ll} \text{if} \quad r < T_{\min} \ or \ r > T_{\max} & \text{then, Alarm, fault is detected} \\ \text{if} \quad T_{\min} \leq r \leq T_{\max} & \text{then, No Alarm, fault-ree} \end{array}$$

where the threshold values $T_{\min} < 0$, $T_{\max} > 0$ denote the minimum and maximum values of the threshold T.

The residuals are usually stochastic variables $r(t)$ with a certain probability density function $p(r)$, mean value and variance (Isermann, 2006)

$$\mu_r(N) = \frac{1}{N}\sum_{k=1}^{N} r(k); \qquad \sigma_r^2(N) = \frac{1}{N-1}\sum_{k=1}^{N}(r(k) - \mu_r)^2 \tag{31}$$

In order to limit the averaging over a *time window* of length ω, the mean then becomes

$$\mu_r(N) = \frac{1}{\omega}\sum_{k=N-\omega+1}^{N} r(k) \tag{32}$$

Correspondingly, the window estimates of the variance yield

$$\sigma_r^2(N) = \frac{1}{\omega - 1}\sum_{k=N-\omega+1}^{N}(r(k) - \mu_r)^2 \tag{33}$$

and standard deviation can be written as

$$\sigma_r(N) = \sqrt{\frac{1}{\omega - 1}\sum_{k=N-\omega+1}^{N}(r(k) - \mu_r)^2} \tag{34}$$

Then, the threshold values are determined by using the residual signal in 'no fault' condition as

$$\begin{cases} T_{\max} = \kappa\sigma_r(N) \\ T_{\min} = -\kappa\sigma_r(N) \end{cases} \tag{35}$$

With e.g. $\kappa \geq 2$, to detect the change just by observing the average $\mu(r, t)$. In selecting the threshold, a comparison has to be made between the detection of relatively small changes and false alarms. In 'no-fault' condition, the residual signal is a zero mean random variable (noise).

4. Implementation and experimental results

In order to demonstrate the validity of the proposed fault detection method, some experimental tests are performed.

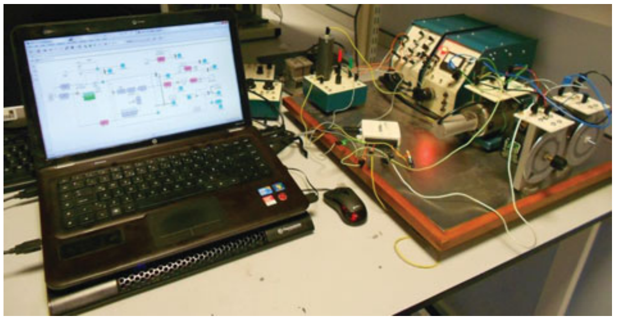

Figure 5. Experimental set-up.

Experimental set-up is illustrated in Figure 5. MS150 Modular Position Servo System is used as the test stand, which is a unique medium for the study of theory and practice of automatic control systems. A data acquisition card (NI USB-6009, 14-bit, 48 kS/s) is used to communicate between the plant and the computer. The operating range of the card is ±10 V for input data and 0–5 V for control outputs.

DC motor parameters that have been taken from the manufacturer (Feedback Instruments Ltd.) are shown in Table 1. The corresponding transfer function (input is armature voltage, output is speed) of DC motor is found as

$$T(s) = \frac{290800}{s^2 + 1076s + 258200}$$

The error signal between real measurements and transfer function model is shown in Figure 6. The minimum variance is calculated as 6.2350e−004.

The signal to be estimated by NMV estimation algorithm is the output speed of the DC motor. The nonlinearities faced by the estimated signal in the transmitting channel path will be Coulomb friction and dead zone as shown in Figure 7. Dead zone nonlinearity is a common type of nonlinear characteristic that occurs in many practical applications. Such characteristic is typical of valves and some amplifiers at low input signals and occurs in many mechanical systems. For the present case, the rotational system exhibits this type of nonlinearity when the armature voltage is around zero. When a continuous signal applied to the armature of the driving DC motor goes through zero volts, the system stays motionless for some time. This is a result of the fact that the mechanical system cannot respond immediately to input signal commands when it is at rest.

Table 1. DC motor parameters.

Armature resistance	$R_a = 5.5$ ohm
Armature inductance	$L_a = 7.2 \times 10^{-3}$ H
Moment of inertia	$J = 32 \times 10^{-6}$ kg m^2
Back EMF constant	$K = 67 \times 10^{-3}$ Vs/rad^{-1}
Friction constant	$B = 10 \times 10^{-3}$ Nm

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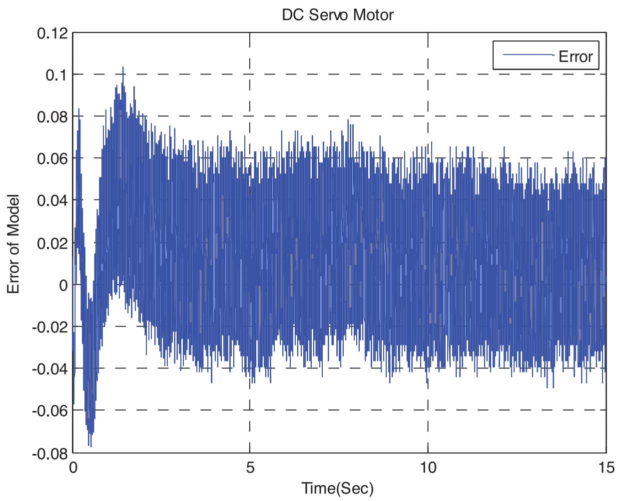

Figure 6. Error signal of the model.

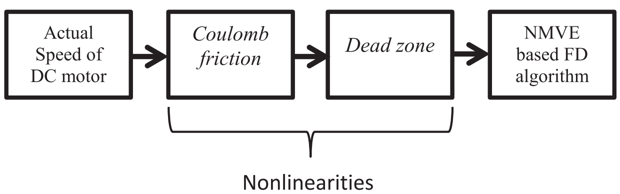

Figure 7. Nonlinearities in measurement channel.

The Coulomb friction causes mechanisms to be resistant to move from rest. A well-known phenomenon concerned with Coulomb friction is that the rotational system will not start to move apparently until the driving torque is large enough to break the static friction torque (Kara & Eker, 2004). The mathematical models used, during this implementation, are given as follows:

$$
\begin{aligned}
W_s &= \frac{0.0047z^{-1} + 0.0047z^{-2}}{1 - 2z^{-1} + z^{-2}};\\
W_n &= \frac{0.02788z^{-1} - 0.02788z^{-2}}{1 - 1.971z^{-1} + 0.9721z^{-2}}\\
G_0 &= 0.0017 - 0.0039z^{-1} + 0.0028z^{-2} - 0.00055z^{-3}\\
A &= 0.12 - 0.48z^{-1} + 0.72z^{-2} - 0.47z^{-3} + 0.12z^{-4}\\
Y_f &= \frac{0.03258 - 0.0882z^{-1} + 0.0789z^{-2} - 0.02331z^{-3}}{1 - 3.971z^{-1} + 5.914z^{-2} - 3.915z^{-3} + 0.9721z^{-4}}\\
\mathcal{F}_{c0}^{-1} &= \frac{30 - 30z^{-1}}{1 - 0.2565z^{-1}}
\end{aligned}
$$

Real-time data are collected by using Labview and the proposed NMV estimation-based fault detection method is implemented in Simulink of Matlab software. Simulink model of the developed method is shown in Figure 8. The produced control input is sent to the pre-amplifier unit of the DC servo system and output speed is measured in open loop operation. The sampling period is taken as a 0.001 s. The computation of the estimator is relatively straightforward. The polynomial matrix equations can be solved using the Matlab polynomial toolbox PolyX.

Under normal operation condition (fault-free), actual signal and estimated signal are illustrated in Figure 9. Tuning filter response is shown in Figure 10. Calculated residual signal and confidence level threshold are depicted in Figure 11. As shown in the figure, residual signal is under the threshold. It means system is under normal operation.

Two types of faults are applied to validate the effective of the proposed NMV estimator in fault detection implementation.

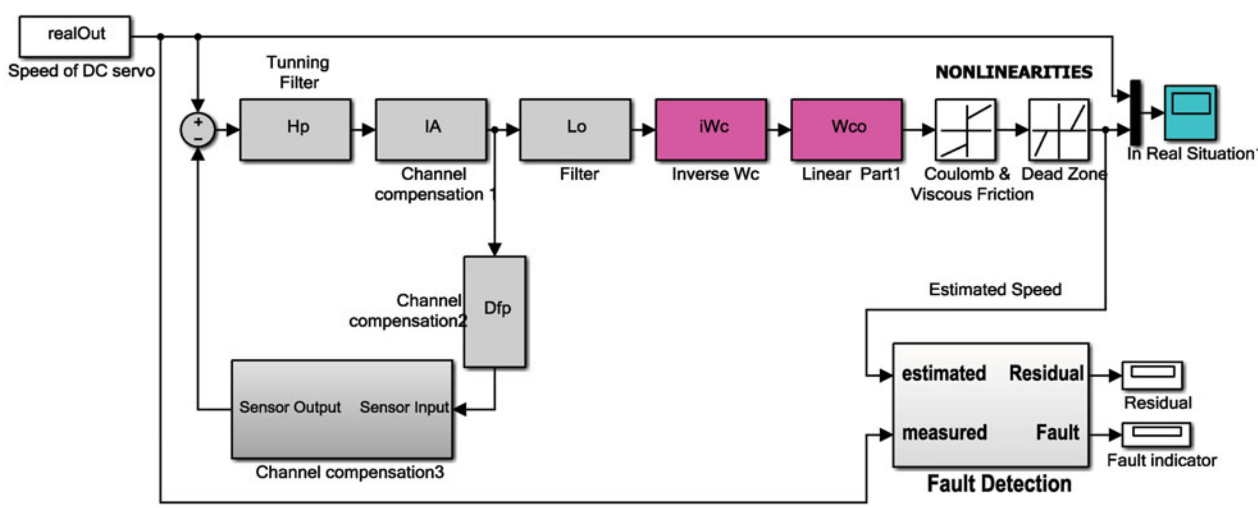

Figure 8. Simulink model of the proposed method.

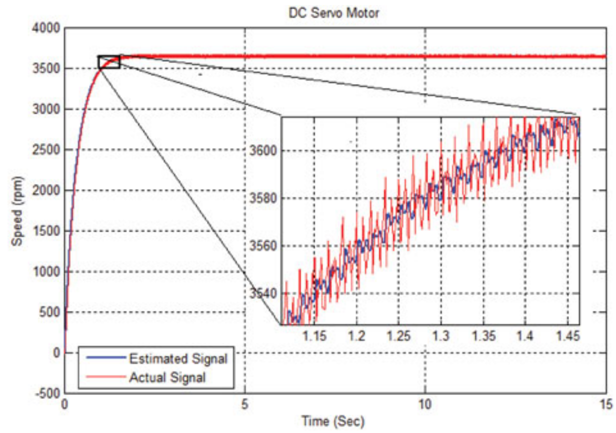

Figure 9. Measured and estimated signal (no fault).

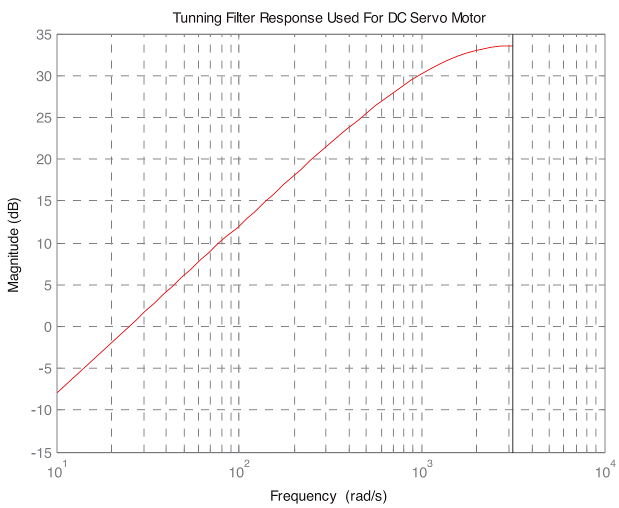

Figure 10. Tuning filter frequency responses.

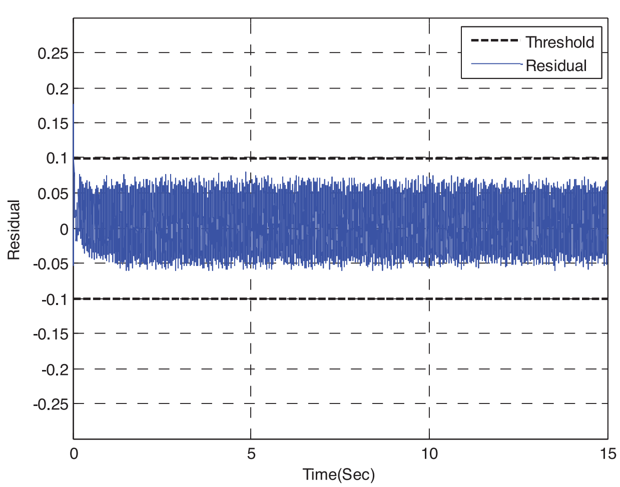

Figure 11. Residual signal with thresholds (no fault).

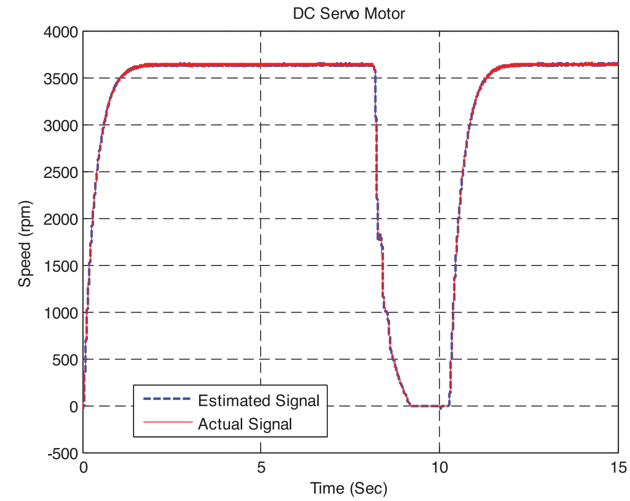

Figure 12. Actual and estimated signal (faulty).

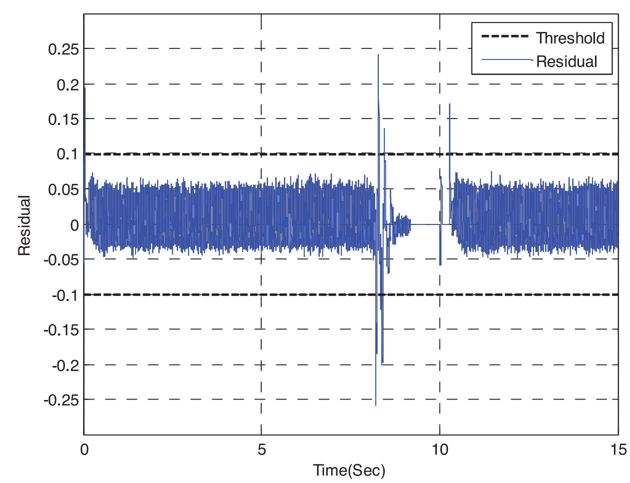

Figure 13. Residual signal with thresholds (faulty).

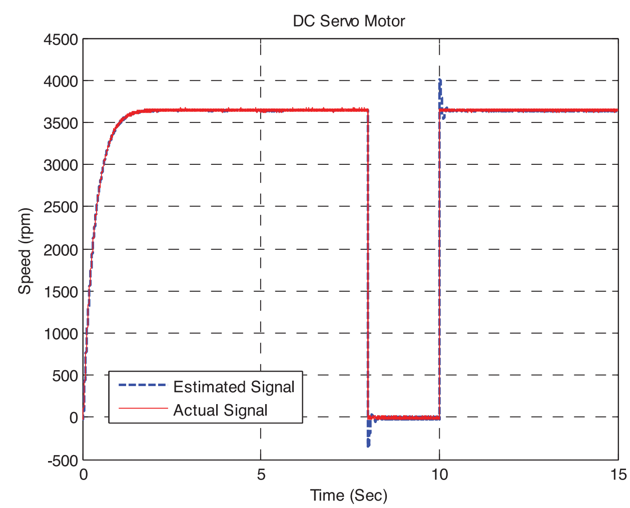

Figure 14. Actual and estimated signal (faulty).

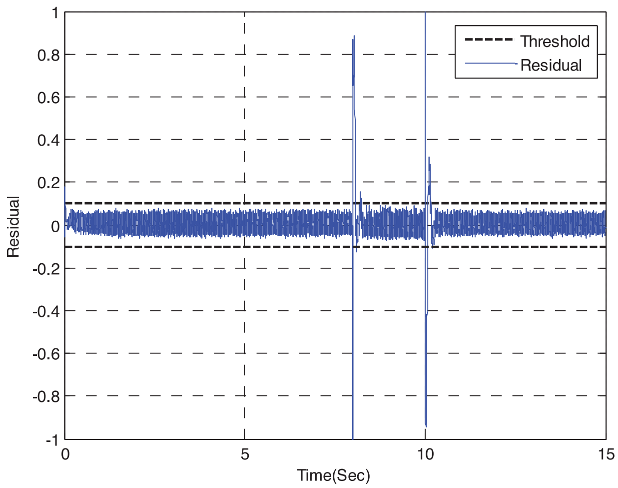

Figure 15. Residual signal with thresholds (faulty).

4.1. *Actuator fault*

For the actuator fault, control signal input cable is broken for a while when the system runs under the normal condition. After applied actuator fault, actual signal and estimated signal are illustrated in Figure 12. Calculated residual signal and confidence level threshold are dedicated in Figure 13. Fault has been detected successfully as shown in Figure 13.

4.2. *Sensor fault*

For the sensor fault, speed sensor cable is broken for a while when the system runs under the normal condition. After the sensor fault is applied, actual signal and estimated signal are as illustrated in Figure 14. Calculated residual signal and confidence level threshold are dedicated in Figure 15. Fault has been detected successfully as shown in Figure 15.

5. Conclusions

An NMV estimator-based fault detection system for nonlinear systems has been developed. The NMV estimator is used to generate the residual signal which indicates possible fault conditions in the system. The NMV estimator has some benefits relative to some other nonlinear estimators in three respects: i.e. it requires less computational cost, easy to implement and to tune. The algorithm is applied experimentally to nonlinear DC servo system. The experimental results show that the method has a good performance in detecting faults at either sensor or actuator.

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Notes on contributors

Alkan Alkaya received his BS degree in 2001 from Gaziantep University, Gaziantep, Turkey, MSE degree in 2005 from Mersin University, Mersin, Turkey, and PhD degree in 2012 from Çukurova University, Adana, Turkey, all in electrical and electronics engineering. He studied as a visiting researcher at the University of Strathclyde, Glasgow, UK, between 2012 and 2013. He joined the faculty of Mersin University in 2001 as a research assistant and is currently an assistant professor in the Department of Electrical and Electronics Engineering, Mersin University, Turkey. His research interests include nonlinear estimation, system identification, fault detection, optimal control and renewable energy sources.

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