Luenberger observer-based sensor fault detection: online application to DC motor

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Abstract: Fault detection and diagnosis (FDD) are very important for engineering systems in industrial applications. One of the most popular approaches is model-based fault detection. Recently, many techniques have been proposed in the FDD area. However, there are still very few reported applications or real-time implementations of the schemes. This paper presents online sensor FDD based on the model-based approach using a Luenberger observer and experimental application on a permanent magnet DC motor. Different kinds of faults are simulated on the motor and experiments are performed to detect the faults. The experimental results demonstrate that this approach could significantly detect the time and size of the faults.

Key words: Fault detection, observer, DC motor, experimental application

1. Introduction

In the literature, fault detection is used to indicate that something is wrong in the monitored system and fault diagnosis is used to determine the location of the fault [1–5]. Fault detection and diagnosis (FDD) is becoming more and more important for process monitoring because of the increasing demand for higher performance, as well as for the increased safety and reliability of dynamic systems. FDD deals with the timely detection, diagnosis, and correction of abnormal conditions of faults in a process.

The classical approaches are the limit or trend checking of some measurable output variables. More advanced methods include data-driven–based fault detection [6–10], most heavily used in many chemical and manufacturing industries. Principal component analysis (PCA) and partial least squares (PLS) are multivariate statistical methods that generalize the univariate control charts that have been applied for decades [11,12].

Other methods rely on analytical redundancy (model-based approaches) [5,8,13,14], which is the comparison of the actual plant behavior to that expected on the basis of a mathematical model. Model-based fault detection uses a residual signal, which indicates changes between the real process and the process model. It also indicates that the essential problem in model-based FDD is to generate a good residual model describing the behavior of the monitored system. Some different methods based on a dynamic physical model to generate a residual generator, such as, for example, output observers, parity relations, and parameters estimation methods, were investigated in recent research [15–18].

The most widely used approach to generate diagnostic signals (residuals) is observers [19]. Many authors have approached the fault detection and isolation (FDI) problem using Luenberger observers [5,6,20,21]. The basic idea of the observer-based FDD consists of estimating the outputs of the system from the measurement

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using an observer and then constructing residuals via properly weighted output estimation errors. One specific diagnostic signal must be generated per each fault to be detected, each diagnostic signal being sensitive only to one particular fault. In a plant, faults can occur either in the main processing equipment (variation in process parameters) or in the auxiliary equipment (bias or drift in sensors, actuators, controller outputs, etc.). In the case of actuator faults, we lose the ability to control the system through one of the actuators. Sensor faults reduce the reliable measurement information through the loss of a sensor, making the system less observable, while a fault in the process component changes the behavior of the entire plant.

This paper is carried out in order to develop and prove the feasibility of FDI algorithms for DC motor systems. However, there still appears to be a shortage of practical applications, with many researchers favoring the easier and more controllable environment of dynamic simulation. While such approaches have produced impressive results, the difficulties of real-world hardware and signals need to be addressed before model-based schemes are widely adopted by industry.

The major goals of the fault diagnosis methods that are widely implemented in industrial systems are to ensure system reliability and robustness [15,22]. The uncertainty of the system models, the presence of noise, and the stochastic behavior of several variables make it hard to reach these goals. To tackle such kinds of problems, we propose a scheme for FDD applications.

The scheme is based on a Luenberger observer to generate a residual sensitive to fault occurrences and also to provide a robust fault detection method including a false alarm rejection, which is required for system reliability [22]. This proposed robust observer-based approach is applied for fault diagnosis on real laboratory equipment, such as a permanent magnet DC motor.

The paper is organized as follows. The observer-based fault detection is presented in Section 2. The next section is devoted to the experimental setup and preliminaries. In Section 4, the experimental application and results of the proposed observer method are provided to report the performance of the fault detection. The conclusion is given in Section 5.

2. Observer-based fault detection

The aim of the observer-based fault detection method is to generate a residual, which is called a fault indicator. The linear state space model of the DC motor is given by:

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) \\ y(t) = Cx(t) \end{cases}, \tag{1}$$

with the input $u(t) \in \Re^r$, the state x(t) $\in \Re^n$, and the output y(t) $\in \Re^m$. $\Re$ denotes the real number vector. Assume that A $\in \Re^{nxn}$, B $\in \Re^{nxr}$, and C $\in \Re^{mxn}$ are known plant matrices. r, m, and n denote the number of inputs, number of states, and number of outputs, respectively.

The observer can be designed as follows to provide the system observability:

$$\begin{cases} \dot{\hat{x}}(t) = A\hat{x}(t) + Bu(t) + K(y(t) - \hat{y}(t)) \\ \hat{y}(t) = C\hat{x}(t) \end{cases}, \tag{2}$$

where $\hat{x}$, $\hat{y}$ are the estimated system state and output, respectively. K is the matrix of the observer feedback gains that is designed to provide the required performance of the observer and K $\in \Re^+$, $\Re^+$ denotes a set of positive real numbers. Residuals are generated by comparing the measured system output y(t) and the estimated

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system output $\hat{y}(t)$ to detect the unpermitted behavior of the system. The configuration of an observer-based residual generator for fault detection is illustrated in Figure 1, where $f(t)$, $d(t)$, and $r(t)$ denote the fault, disturbance, and residual, respectively. Subtracting Eq. (2) from Eq. (1) gives:

$$\begin{cases} \dot{x}(t) - \dot{\hat{x}}(t) = Ax(t) - A\hat{x}(t) - K(Cx(t) - C\hat{x}(t)) \\ \qquad = (A - KC)(x(t) - \hat{x}(t)) \end{cases} \tag{3}$$

The state estimation error $\tilde{x}$ can be calculated as:
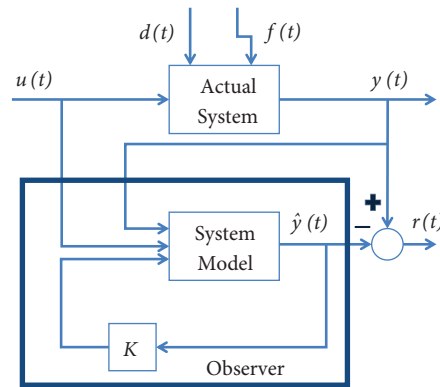
$$\tilde{x}(t) = x(t) - \hat{x}(t). \tag{4}$$

Figure 1. Use of the observer to generate the residual.

Next, Eq. (2) can be rewritten as:

$$\dot{\tilde{x}}(t) = (A - KC)\hat{x}(t). \tag{5}$$

Since it has been assumed that the pair (A, C) is observable, the observer gain matrix K can be selected such that $(A - KC)$ is a stable matrix.

$$r(t) = y(t)\hat{y}(t). \tag{6}$$

Hence, the residual signal $r(t)$:

Fault detection can be carried out as follows:

$$\begin{cases} r(t) = 0, & \text{no fault occured} \\ r(t) \neq 0, & \text{fault has occured} \end{cases} \tag{7}$$

2.1. DC motor modeling

The continuous time state variable linear model of the DC motor is as follows:

$$\begin{cases} \dot{X}(t) + AX(t) + BU(t) \\ Y(t) = CX(t) \end{cases} \tag{8}$$

The 2 states considered are the armature current I_a and the angular velocity of the shaft speed ? of the DC motor. The input is the armature voltage $U(t)$, and the state vector, $X(t)$, has been selected such that:

$$X(t) = \begin{bmatrix} I_a \\ \omega \end{bmatrix}. \tag{9}$$

The state transition, input, and observation matrices for the model are:

$$A = \begin{bmatrix} -R_m / L_m & -K_b / L_m \\ K_t / J_m & B_m / J_m \end{bmatrix} \quad B = \begin{bmatrix} 1 / L_m \\ 0 \end{bmatrix} \quad C = \begin{bmatrix} 0 & 1 \end{bmatrix}, \tag{10}$$

where L_m is the motor winding inductance, K_b is the motor back-emf constant, K_t is the motor torque constant, J_m is the rotor inertia, and B_m is the mechanical damping factor.

The parameters are calculated using open-loop input-output data from an experimental real system and from the system in the Simulink model, and then the MATLAB Parameter Estimation Toolbox is used to compute the unknown parameters of the motor, as presented in the Table.

Table. Estimated DC motor parameters

R_m	2.4021 Ω
L_m	0.0197991 mH
K_b	1.0452 V s rad^{-1}
K_t	1.04 Nm A^{-1}
J_m	0.076058 kg m^{-2}
B_m	0.069858

3. Experimental setup and preliminaries

The validity of the observer-based fault detection method is tested through an experimental system, as shown in Figure 2. For this purpose, a series of experiments are carried out using a DIGIAC 1750 process control set, a data acquisition card, and a computer. In each of these experiments, a distinct fault detection approach is used with its corresponding configuration setup. The process control set has a DC motor and a tachogenerator connected via a shaft, on which various kinds of speed sensors are mounted. The computer used has a Pentium IV, a 2-GHz microprocessor, 1 GB of RAM, and a 256-MB display adapter.


Figure 2. A scene from the laboratory.

The specifications of the DC motor are given in the Table. The speed of the motor is measured with the output of the tachogenerator voltage, which is directly proportional to the motor speed. The measured speed data are then transferred to the computer by a data acquisition card (DAQ-National Instruments, Model PCI-6229, 250 kHz in speed, 16 bits), and then the proposed fault detection methods are implemented in the Simulink toolbox of MATLAB and applied to the measured data.

4. Experiments and results

To validate the observer-based fault detection method, a series of experiments are carried out using a DIGIAC 1750 process control set. All of the experiments are performed with 6 V of input voltage and sampling time of $T_s = 5$ ms. The measured signal and calculated residuals are employed without filters to show the robustness of the designed observer model.

A DC motor model is required for observer-based fault detection methods. A DC motor model is built in the MATLAB/Simulink environment. A functional diagram of the overall observer-based fault detection method is demonstrated in Figure 3 After the model is built, the residuals are generated by feeding the input data into the full-order estimator, monitoring the corresponding estimated outputs from the model, and comparing the model outputs with the actual measured values. The errors are considered as the residuals. Thresholds for the detection and diagnosis are set by considering the maximum values reached by the residuals over a range of tests. Once the residual crosses over a certain threshold, an alarm will be triggered to indicate a fault.
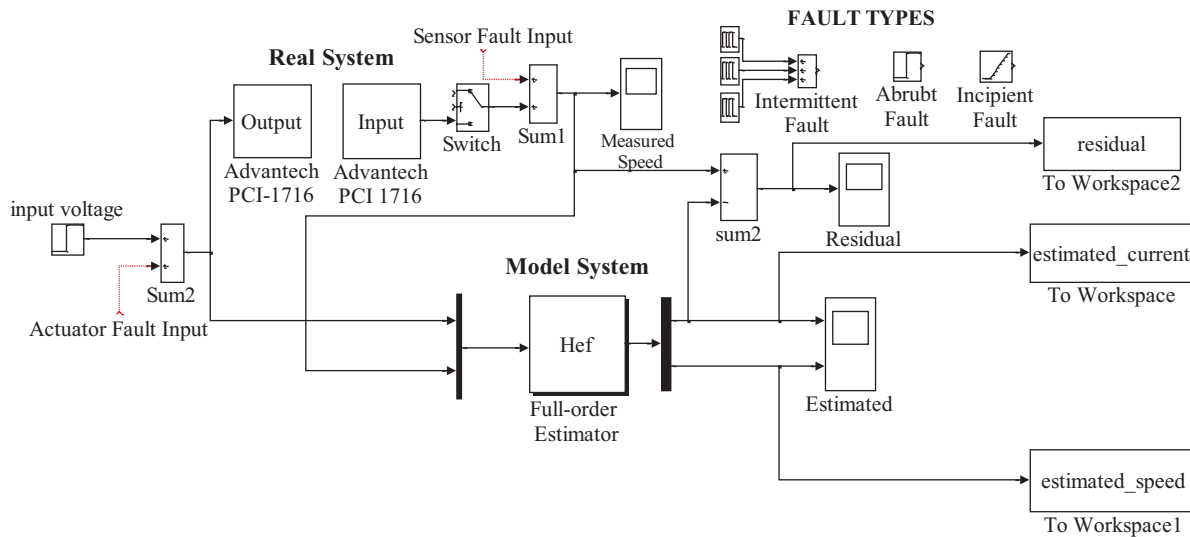
Figure 3. Simulink model of the observer-based fault detection method.
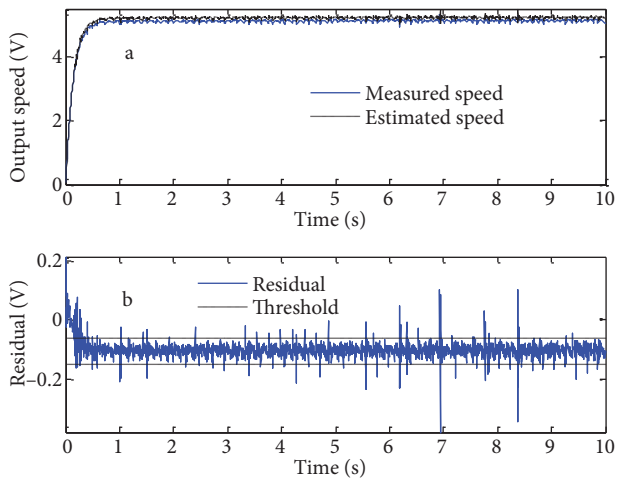
The measured and estimated speed output of the DC motor is shown in Figure 4a and the calculated residual is illustrated in Figure 4b, when there is no fault in the system.

Figure 4b shows that the magnitude of the residual need not be exactly 0 due to the presence of noise in the instruments and also due to errors in the observer design parameters. Hence, to avoid false alarms, a threshold with upper magnitude of –0.06 and lower magnitude of –0.15 is selected for the residual.
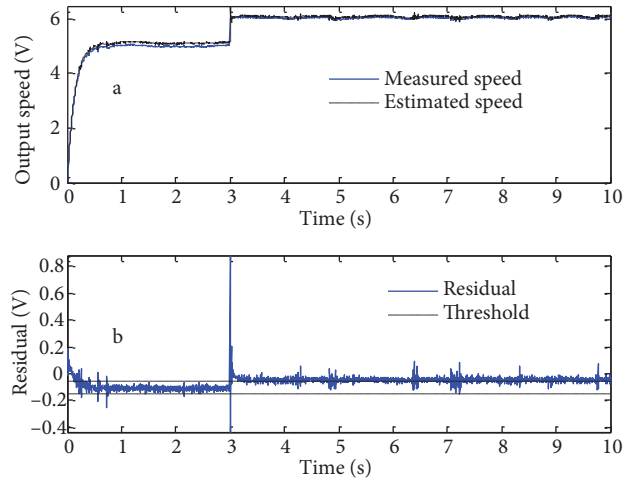
The fault is modeled as a stepwise function and applied to the sensor fault input, as shown in Figure 3. An abrupt fault is applied to the measured sensor output at 3 s. The responses of the measured and estimated outputs are illustrated in Figure 5a and the fault indicator residual is shown in Figure 5b.

In this case, it is observed that the magnitude of the residual shown in Figure 5b increases above the threshold value, signaling the fault of the speed sensor.

The fault is modeled as a ramp function and applied to the sensor fault input, as shown in Figure 3. An incipient fault is applied to the measured sensor output at 3 s. The responses of the measured and estimated outputs are shown in Figure 6a and the fault indicator residual is shown in Figure 6b.

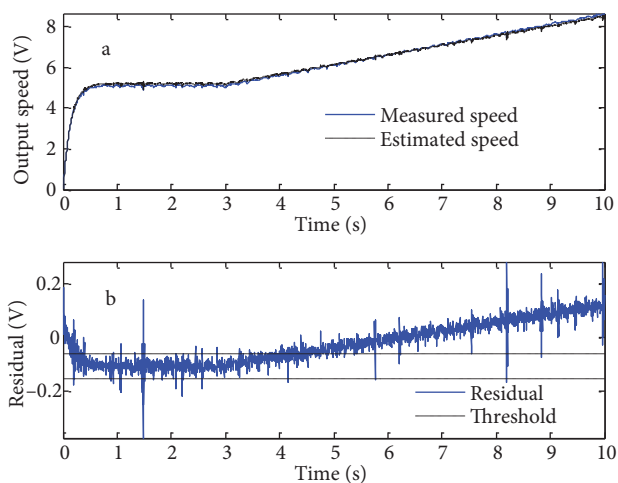**Figure 4.** Fault free case: a) measured and estimated outputs, b) residual.

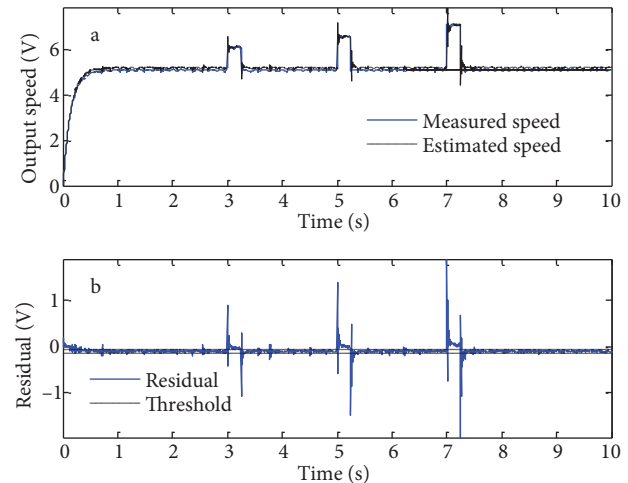**Figure 5.** Abrupt fault: a) measured and estimated outputs, b) residual.

In this case, it is observed that the magnitude of the residual shown in Figure 6b incipiently increases at 3.5 s above the threshold value, signaling the fault of the speed sensor. Hence, it is assumed that better performance would be achieved by calculating the accurate model parameters.

An intermittent fault is generated as a combination of the impulses at different amplitudes and applied to the sensor fault input, as shown in Figure 3. The fault is applied to the measured sensor output at 3, 5, and 7 s, with amplitudes of 1, 1.5, and 2, respectively, each time during 0.25 s. The responses of the measured and estimated outputs are shown in Figure 7a and the fault indicator residual is shown in Figure 7b.

It is observed that the magnitude of the residual shown in Figure 7b increases above the threshold value at the applied fault time and size.

Figure 6. Incipient fault: a) measured and estimated outputs, b) residual.


Figure 7. Intermittent fault: a) measured and estimated outputs, b) residual.

The sensor failure is generated by disconnecting the speed sensor at 3 s under steady-state conditions. The sensor is reconnected after 1 s. This is implemented as online. The responses of the measured and estimated

outputs are shown in Figure 8a and the fault indicator residual is shown in Figure 8b for the sensor failure scenario.

The magnitude of the residual, shown in Figure 8b, decreases under the threshold value at the applied fault time. From Figure 8b, it can be observed that the generated residual signals are sensitive to the faults under consideration.
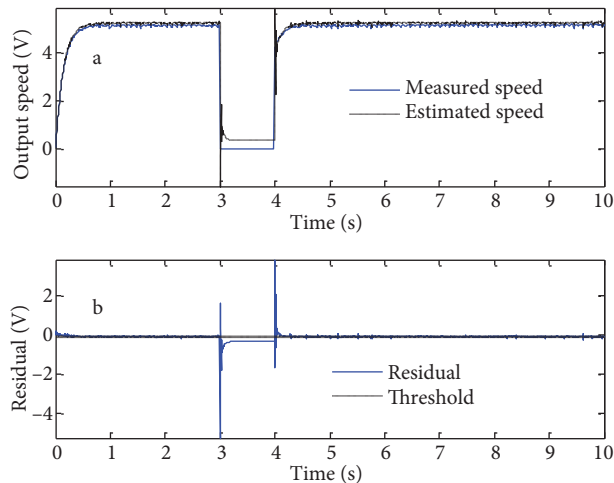
Figure 8. Sensor failure: a) measured and estimated outputs, b) residual.

5. Conclusions

FDD is becoming more and more important for process monitoring because of the increasing demand for higher performance, as well as for the increased safety and reliability of dynamic systems. FDD deals with the timely detection, diagnosis, and correction of abnormal conditions of faults in a process. The early detection of the occurrence of faults is critical in avoiding product deterioration, performance degradation, major damage to the machinery itself, and damage to human health or even loss of lives.

The development and application of an observer-based scheme for fault detection has been demonstrated by application to an electromechanical system (DC motor). The observer is designed using a measured motor speed sensor. Abrupt, incipient, intermittent, and sensor failures are applied to the output of the DC motor systems. Residuals are generated by subtracting the real output speed from the estimated output speed to detect the unpermitted behaviors, which are called faults. The experimental results show that observer-based methods are more suitable for additive faults (abrupt, intermittent).

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