# Serial Communication-Based Fault Diagnosis of a BLDC Motor Using Bayes Classifier

**Suhk-Hoon Suh and Kwang-Joon Woo**

**Abstract**: This paper presents a serial communication based fault diagnosis scheme for a brushless DC (BLDC) motor using parameter estimation and Bayes classifier. The presented scheme consists of a smart network board, and a fault detection and isolation (FDI) master. The smart network board is installed near the BLDC motor drive system to acquire motor data and transmit motor data to the FDI-master via serial communication channel. The FDI-master estimates BLDC motor resistance to detect symptom of faults, and assign symptom to fault type using Bayes classifier. In this scheme, since communication time delay has a serious effect on performance, periodic and fixed communication protocol is designed. Hence, the delay time is priory known. By experiment result, presented scheme was verified.

**Keywords**: Fault diagnosis, parameter estimation, Bayes classifier, serial communication.

## 1. INTRODUCTION

With the demands of reliable servo system, the application of a brushless DC (BLDC) motor has been more and more increased. Nevertheless, a BLDC motor can fail. In particular, overload and overheating can damage the stator coil, thus resulting in lower performance. Moreover, necessary sensors for position detection, e.g., Hall sensors, can fail as well, while damaged or broken bearings may result in increased friction. In closed-loop operation of servo systems, these faults often remain hidden by feedback. Only if the whole device fails, i.e., the motor stops turning, does the failure become visible. Therefore, it is desirable to detect an incipient fault as early as possible to perform maintenance before the failure of the device occurs [1].

To detect BLDC motor faults, dynamic system fault detection and isolation (FDI) methods are often used. The purpose of dynamic system FDI is detecting a fault as it occurs and identifying the faulty component to perform appropriate maintenance before critical system malfunctions are occurred. The FDI can be applicable to plants, which demands a high degree of system reliability such as power plants and avionics systems. Therefore, FDI has attracted great attention from both academic and industrial communities.

Using the fieldbus, control network, cables of control system are replaced with networks. The fieldbus network has advantages in the number of cable line and EMI problem. However, data sent over control networks differ from those encountered in networks for data communication purposes [2]. In data networks, large sets of data messages are transmitted occasionally at high data rates for short intervals of time. In contrast, data in control networks are continuously sent out at relatively constant data rates. Furthermore, there are crucial real-time requirements to achieve certain control performance. Hence, communication methods, or protocols, used in data networks are not necessarily appropriate for control use. In the past decade, by groups of companies and professional organizations, much effort has been made for standardization of protocols [3].

Xiang-Qun *et al.* [4] discussed DC motor fault detection and diagnosis by parameter estimation and neural network. Where, the electromechanical parameters of the motor can be obtained from the estimated model parameters, and the relative changes of electromechanical parameters are used to detect motor faults. Neural network is used to isolate faults based on the patterns of parameter changes. Moseler *et al.* [1,5,6] presented a real time fault detection for a BLDC motor driving a mechanical actuation system. Where, they drive a mathematical model which is based on the bridge supply voltage, current and the rotor velocity. Suh et al. [7] presented observer-based fault detection scheme for a Permanent Magnet Synchronous Motor (PMSM) drive system using serial network. And they proposed fault detection scheme of BLDC motor drive system by estimating BLDC motor resistance using motor input and output data which is transmitted from data acquisition board to host computer over serial communication channel [8].

Manuscript received November 6, 2002; revised March 11, 2003; accepted April 28, 2003. The present research was conducted by the research fund of Dankook University in 2002.

Suhk-Hoon Suh and Kwang-Joon Woo are with the Department of Electronics Engineering, Dankook University (e-mails: shush@dankook.ac.kr, wookj@dku.edu).

In this paper, we presents serial communication based fault diagnosis scheme of a BLDC motor using parameter estimation and Bayes classifier. The presented scheme consists of a *smart network board*, and a *FDI-master*. The *smart network board* is installed near the BLDC motor drive system to acquire motor data and transmit motor data to the *FDI-master* via serial communication channel. By using smart network board, the presented scheme can be applied to amplifier, which have no communication function, or different communication protocols. The *FDI-master*, host computer, estimates BLDC motor parameters. For fault diagnosis, we use mathematical BLDC motor model, which is based on the bridge supply voltage, current and the rotor velocity. In the model, BLDC motor is represented by electrical and mechanical parameters, which are similar to the conventional DC motor model. By estimating electrical parameters, we can get the information about coil and load conditions. Therefore, we choose estimated resistance as a feature data (fault symptom). Using Bayes classifier, fault symptom is mapping to fault types. For the presented scheme, periodic and fixed communication protocol was designed. Hence, the delay time is priory known. By experiment result, we confirm the proposed scheme under discrete fault occur case.

In Section 2, we introduce the parameter estimation algorithm and the Bayes classifier. Section 3 addresses communication protocols. In Section 4, we describe fault diagnosis scheme. The experiment and results are stressed in Section 5, and Section 6 gives conclusions.

## 2. PARAMETER ESTIMATION AND BAYES CLASSIFIER

### 2.1. BLDC meter model

Moseler *et al.* [1, 5, 6] presented a real time fault detection for a BLDC motor driving a mechanical actuation system. Where, they drove a mathematical model which is based on the bridge supply voltage, current and the rotor velocity. In this paper, we use their model for estimating parameters, so introduce their model [1].

The model is represented as follows:

$$\bar{v} = \frac{2}{3}(R_1 + R_2 + R_3)\bar{i}(t) + \frac{2}{3}(K_{e1} + K_{e2} + K_{e3})\omega_r(t), \tag{1}$$

where $\bar{v}(t) = v_{pwm}(t)$ ($v_{pwm}(t)=pwm(t)\cdot V_{supply}$, $pwm(t) \in [0,1]$), $R_i$ and $K_{ei}$ (i=1, 2, 3) is resistance and back-EMF constant of each coil. Substituting $2/3\cdot(R_1 + R_2 + R_3)$ with $R$ and $2/3\cdot(k_{e1} + k_{e2} + k_{e3})$ with $K_E$, leads to the equation

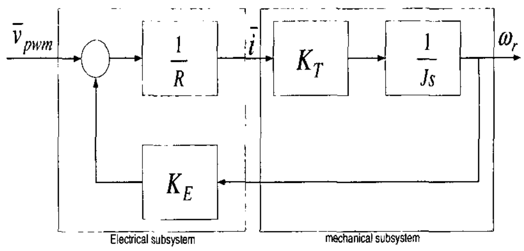



Fig. 1. Block diagram of the motor model.

$$\bar{v}(t) = R\bar{i}(t) + K_E\omega_r(t). \tag{2}$$

The average phase current $\bar{i}$ can be driven from the bridge current by considering the power balance

$$v_b \cdot i_b(t) = v_{pwm}(t) \cdot \bar{i}(t) = pwm(t) \cdot v_b \cdot \bar{i}, \tag{3}$$

where $v_b$ and $i_b$ denote bridge supply voltage and bridge current. Hence,

$$\bar{i}(t) = i_b(t) / pwm(t). \tag{4}$$

Fig. 1 represents the block diagram of the model, where $K_T$ is torque constant and $J$ denotes the inertia of the rotor.

### 2.2. Parameter estimation

The quantitative knowledge, a mathematical model of a system is useful in detection fault. If the system is represented with the mathematical model, we can estimate model parameters based on input and output signals ($u(t)$ and $y(t)$). The least square algorithm is a very simple and robust method of estimating parameters [9].

Perhaps the most basic relationship between the input and output is the linear difference equation:

$$\begin{aligned} y(t) + a_1 y(t-1) + \ldots + a_n y(t-n) \\ = b_1 u(t-1) + \ldots + b_m u(t-m). \end{aligned} \tag{5}$$

A useful way to see (5) is to view it as a way of determining the next output value given previous observations:

$$\begin{aligned} y(t) = -a_1 y(t-1) - \ldots - a_n y(t-n) \\ + b_1 u(t-1) + \ldots + b_m u(t-m). \end{aligned} \tag{6}$$

For more compact notation we introduce the vectors:

$$\theta = [a_1 \ \ldots \ a_n \ b_1 \ \ldots \ b_m]^T, \tag{7}$$

$$\varphi(t) = [-y(t-1) \ \cdots - y(t-n) \ u(t-1) \ \cdots \ u(t-m)]^T. \tag{8}$$

With these, (6) can be rewritten as

$$y(t) = \varphi^T(t)\theta. \tag{9}$$

To emphasize that the calculation of $y(t)$ from past data (6) indeed depends on the parameters in $\theta$, we shall rather call this calculated value $\hat{y}(t,\theta)$ and write

$$\hat{y}(t,\theta)=\varphi^T(t)\theta. \tag{10}$$

Suppose for a given system that we do not know the values of the parameters in $\theta$, but that we have recorded inputs and outputs over a time interval $1 \le t \le N$:

$$Z^N=\{u(1),y(1),\dots,u(N),y(N)\}. \tag{11}$$

An obvious approach is then to select $\theta$, so as to fit the calculated values $\hat{y}(t,\theta)$ as well as possible to measured outputs by the least squares method:

$$\min_{\theta} V_N(\theta,Z^N), \tag{12}$$

where

$$\begin{aligned} V_N(\theta,Z^N)&=\frac{1}{N}\sum_{t=1}^{N}(y(t)-\hat{y}(t,\theta))^2 \\ &=\frac{1}{N}\sum_{t=1}^{N}(y(t)-\varphi^T(t)\theta)^2. \end{aligned} \tag{13}$$

We shall denote the value of $\theta$ that minimizes (13) by $\hat{\theta}_N$:

$$\hat{\theta}_N=\arg\min_{\theta} V_N(\theta,Z^N), \tag{14}$$

where "arg min" means the minimizing argument, i.e., that value of $\theta$ which minimizes $V_N$.

Since $V_N$ is quadratic in $\theta$, we can find the minimum value easily by following equation.

$$\hat{\theta}_N=\left[\sum_{t=1}^{N}\varphi(t)\varphi^T(t)\right]^{-1}\sum_{t=1}^{N}\varphi(t)y(t). \tag{15}$$

(15) can be restated as the recursive least square (16) to (18)

$$\hat{\theta}(t)=\hat{\theta}(t-1)+L(t)\left[y(t)-\varphi^T(t)\hat{\theta}(t-1)\right] \tag{16}$$

$$L(t)=\frac{P(t-1)\varphi(t)}{\lambda(t)+\varphi^T(t)P(t-1)\varphi(t)}, \tag{17}$$

$$P(t)=\frac{1}{\lambda(t)}\left[P(t-1)-\frac{P(t-1)\varphi(t)\varphi^T(t)P(t-1)}{\lambda(t)+\varphi^T(t)P(t-1)\varphi(t)}\right] \tag{18}$$

where $L(t)$, prefilter, is to allow extra freedom in dealing with non-momentary properties of the prediction errors. In order to let the parameter estimation follow changing in the system, uses a forgetting factor $\lambda$, which means that older values of $u(t)$ and $y(t)$ do not have so much weight as the newer values. The forgetting factor $\lambda$ is normally chosen between 0.95 and 1 [10].

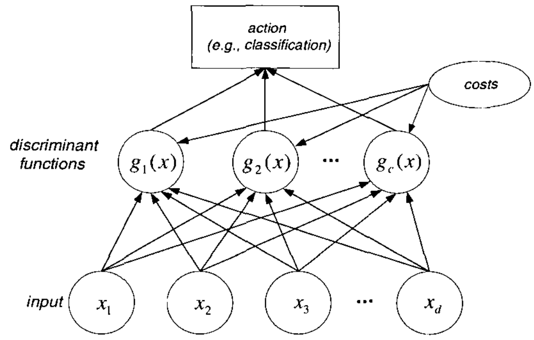



Fig. 2. The functional structure of a statistical pattern classifier.

2.3. The bayes classifier

There are many different ways to represent pattern classifiers [11]. One of the most useful is in terms of a set of discriminant functions $g_i(x)$, $i=1, \cdots, c$. The classifier is said to assign a feature vector $x$ to class $\omega_i$ if

$$g_i(x)>g_j(x) \qquad \text{for all } j\neq i. \tag{19}$$

Thus, the classifier is viewed as a network or machine that computes $c$ discriminant functions and selects the category corresponding to the largest discriminant. A network representation of a classifier is illustrated in Fig. 2.

The fundamental principle of a Bayes classifier is Bayes rule, shown in (20)

$$P(\omega_i\mid x)=\frac{p(x\mid\omega_i)P(\omega_i)}{\sum_{j=1}^{c}p(x\mid\omega_j)P(\omega_j)}. \tag{20}$$

Bayes rule shows how the information of known probability density functions $p(x|\omega_i)$ and a priori probabilities $P(\omega_i)$ can be used to calculate the a posteriori probability $P(\omega_i|x)$.

The minimum-error-rate classification can be achieved by use of discriminant functions,

$$g_i(\mathrm{x}) = \ln P(x|\omega_i) + \ln P(\omega_i), \quad \text{where } i=1, \cdots, c, \tag{21}$$

and this expression can be readily evaluated if the densities $p(x|\omega_i)$ are multivariate normal - that is, if $p(x|\omega_i) \sim N(\mu_i, \Sigma_i)$. In this case, we have

$$\begin{aligned} g_i(x)=&-\frac{1}{2}(x-\mu_i)^t\textstyle\sum_i^{-1}(x-\mu_i)-\frac{d}{2}\ln 2\pi \\ &-\frac{1}{2}\ln|\textstyle\sum_i|+\ln P(\omega_i). \end{aligned} \tag{22}$$

All the necessary information of each class (feature cluster) is contained in the mean vector and covariance matrix. The center of each cluster is determined by the mean vector and the shape of the cluster by the covariance matrix.

The quantity $r^2 = (x-\mu_i)^t \sum_i^{-1} (x-\mu_i)$ from (22) is often called the Mahalanobis distance from an observation $x$ to the center of the cluster $\mu$.

## 3. COMMUNICATION PROTOCOLS

The *FDI-master*, host computer, estimates motor parameters using motor observations, which are transmitted from the *smart network board* over serial communication channel.

In this paper, we design periodic and fixed frame size bit-oriented communication protocol. Because frame is deterministic, the order of data transmission is scheduled and fixed prior to operation. Therefore, the delay time and bandwidth is known. Fig. 3 depicts protocol frame structure, and Table 1 explains each frame field.

The frame consists of SOT, eight motor information bytes, check sum to error detect, and EOT. The communication begins by the *FDI-master's* request, and the *smart network board* sends data every 20 ms. The token is passed from the *FDI-master* to the *smart network board* with request. And the *smart network board* hold token until the *FDI-master* requests return it. Fig. 4 is the communication sequence between the *FDI-master* and the *smart network board.* Fig. 5 depicts the effect of sampling time. From the figure, we can conclude that different sampling time makes different estimated value. Therefore, for estimation parameter using network, fixed sampling time is necessary.


Fig. 3. Protocol structure.

Table 1. Definition of protocol field.

| Byte No. | Field | Define |
|---|---|---|
| 1 | SOT | Start of transmission |
| 2 | Ph1 Cur. H | Phase 1 current high byte |
| 3 | Ph1 Cur. L | Phase 1 current low byte |
| 4 | Ph2 Cur. H | Phase 2 current high byte |
| 5 | Ph2 Cur. L | Phase 2 current low byte |
| 6 | $i_b$-H | Bridge current high byte |
| 7 | $i_b$-L | Bridge current low byte |
| 8 | PWM | PWM |
| 9 | RPM | Rotor speed |
| 10 | CS | Check sum |
| 11 | EOT | End of transmission |

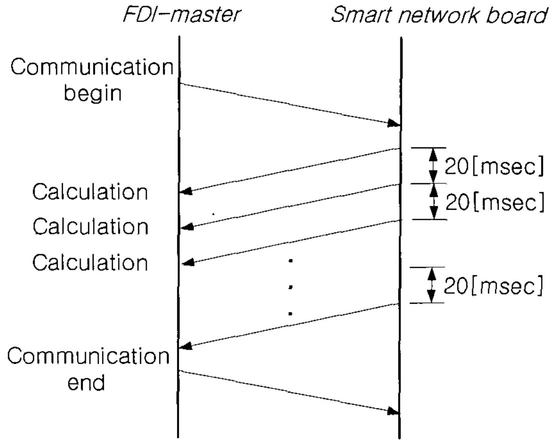



Fig. 4. Communication sequence.

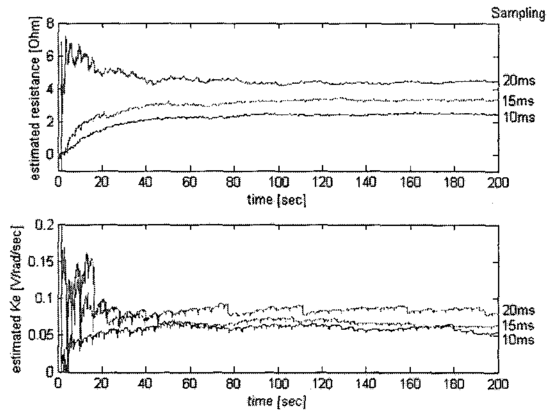



Fig. 5. The effect of sampling time.

In the experiment, we set 19200 baud, 8 data bits, no parity, and 1 stop bit asynchronous protocol, which make 5.7 ms communication time delay.

## 4. FAULT DETECTION AND ISOLATION SCHEME

Fig. 6 shows the proposed FDI scheme. The *Smart network board* acquires bridge current and speed of a BLDC motor. Acquired information is coded to digital value for transmitting. The universal asynchronous receiver and transmitter (UART) converts parallel data to serial data, and transmit data to the *FDI-master* via serial communication channel, RS-485. The *FDI-master* decodes received data, and estimates parameters. Estimated parameters and their known probability knowledge are used for diagnosis faults. Then, the results are displayed on a screen and saved as a file.

The *FDI-master* is designed based on PC and functions are implemented using Visual C/C++, and the *smart network board* is designed using ATmega103 microcontroller with C language. This microcontroller has 8 channels 10 bits A/D converter, timer/counter and UART.

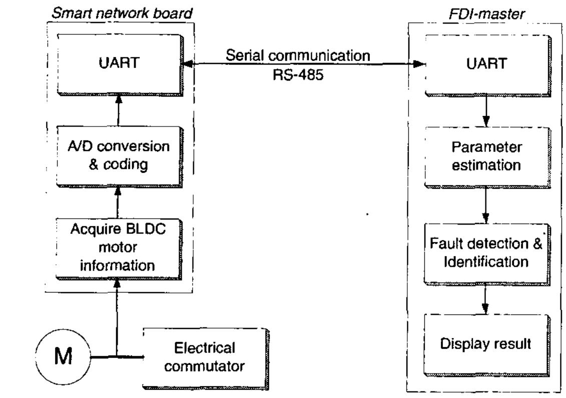



Fig. 6. Fault diagnosis scheme.

## 5. EXPERIMENT AND RESULTS

In the experiment, five fault types are considered. Fault types and fault injection methods are listed in Table 2. The BLDC motor under test is POWERTEC model L42ALA1100700000, and Table 3 shows nominal motor parameters. From (2) $R$ and $K_E$ are calculated as (23) and (24).

$$R = 2/3 \cdot (R_1 + R_2 + R_3) = 2.14\,\Omega, \tag{23}$$

$$K_E = 2/3 \cdot (k_{e1} + k_{e2} + k_{e3}) = 0.04 \text{ V/rpm}. \tag{24}$$

To estimate BLDC motor parameters, $R$ and $K_E$, pseudo-random binary signal (PRBS) is applied as an input and rotor speed is measured as an output. Fig. 7 shows motor input and output signals.

The presented fault diagnosis scheme detects a fault symptom and then, isolates faults. The scheme use variation of the estimated BLDC motor resistance $R$ as the fault symptom, and assign fault symptom to fault type using Bayes classifier. Resistance $R$, fault symptom, is estimated by recursive least square algorithm of 0.9999 forgetting factor, which gives 10000 samples effective window. Bayes classifier requires probability characteristics of fault types to calculate discriminant functions. In the experiment, probability distributions of each faults are assumed as normal distribution, and probability of each fault is 0.2. The mean and variance of each fault type are calculated using over 20000 estimated resistance samples. The five fault types scatter diagram and probability densities are plotted in Fig. 8, and mean and variance of each fault types are listed in table 4. Fig. 8 shows that five faults are statistically independent.

Table 2. Fault types and injection methods.

| Fault No. | Fault Type | Fault Injection Method |
|---|---|---|
| 0 | Fault free | None |
| 1 | Increase of $R_I$ | Add resistance of 2 Ω |
| 2 | Increase of $R_I$ | Add resistance of 4 Ω |
| 3 | Increase load | Add 1Kg load |
| 4 | Increase load | Add 2Kg load |

Table 3. BLDC motor parameters.

| Parameter | Define |
|---|---|
| Resistance, $R$ | 1.07 Ω |
| Inductance, $L$ | 6 mH |
| back-EMF constant, $K_{ei}$ | 0.02 V/rpm |
| torque constant, $K_T$ | 0.175 Nm/A |
| number of pole pairs | 4 |

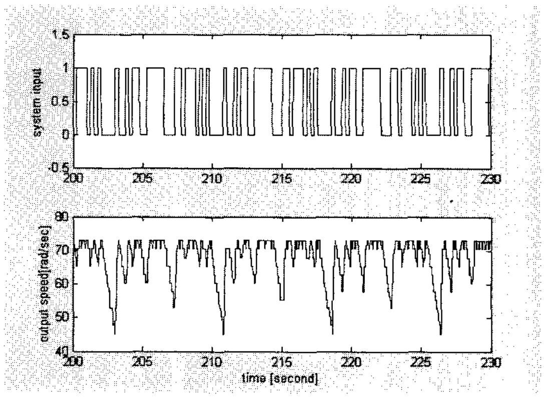



Fig. 7. BLDC motor input and output.

The experiments are performed under 3 scenarios. The first scenario is that the BLDC motor starts with fault number 0 condition. After 300 seconds, 2 Ω resistor is added to BLDC motor one phase, $R_I$. The fault number 1 condition is maintained continuously

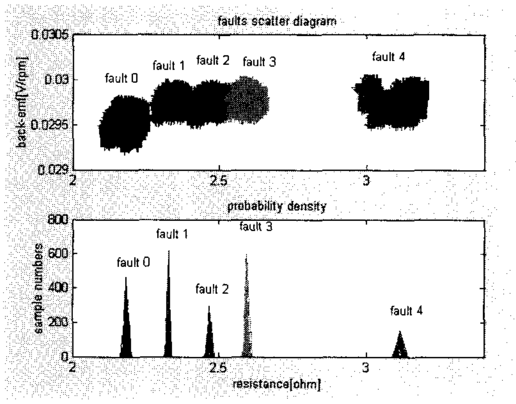



Fig. 8. Faults scatter diagram and probability density.

Table 4. Parameter estimation of fault-free and faulty motor.

| | $R$ [Ω] | | $K_E$ [V/rpm] | |
|---|---|---|---|---|
| Fault No. | Mean [$\mu$] | Variance [$\sigma$] | Mean [$\mu$] | Variance [$\sigma$] |
| 0 | 2.1819 | 8.6493e-4 | 0.0295 | 7.6052e-9 |
| 1 | 2.3264 | 6.4188e-4 | 0.0297 | 5.8079e-9 |
| 2 | 2.4658 | 0.0013 | 0.0297 | 5.9533e-9 |
| 3 | 2.5920 | 6.0077e-4 | 2.5920 | 6.0077e-4 |
| 4 | 3.1124 | 0.0026 | 3.1124 | 0.0026 |

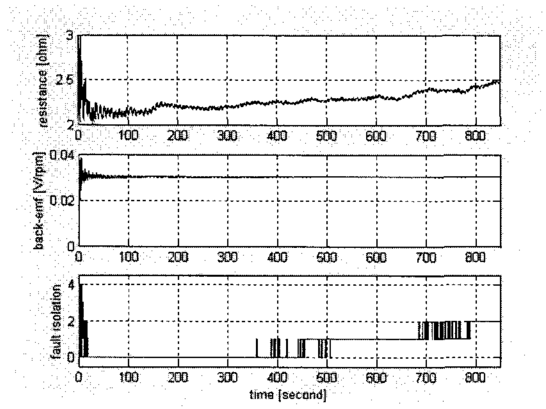



Fig. 9. Resistance varied fault diagnosis.

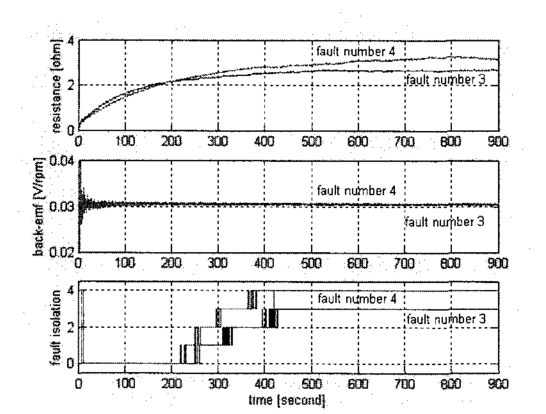



Fig. 10. BLDC motor over load fault diagnosis.

from 300 seconds until 600 seconds. At 600 seconds, 4 Ω resistor is added to $R_l$, fault number 2 is injected. Fig. 9 shows results of scenario 1. The figure shows that Bayes classifier exactly discriminates fault type with about 200 seconds transition time, effects of forgetting factor.

The second scenario is the BLDC motor starts with fault number 3 condition, and the third scenario is the BLDC motor starts with fault number 4 condition. Fig. 10 shows diagnosis results. The results shows, presented scheme exactly isolates fault type 3 and 4 in the steady state condition.

## 6. CONCLUSION

This paper presents serial communication based fault diagnosis scheme of a BLDC motor. In the scheme, we design the *smart network board*, which is installed near the BLDC motor drive system, and the *FDI-master*, host computer. Observations are coded, and transmitted by the *smart network board*, and then, they are decoded by the *FDI-master* for estimation parameters. By using estimated resistance as a fault symptom and Bayes classifier, faults are mapping to fault causes. To design Bayes classifier, probability distributions of each parameter are assumed as normal distribution and mean and variance of five fault types are calculated using previously gathered data. By applying communication channel, we can save cable lines and transmit observations more safely. The experiment is performed under three scenarios, and experiment results show that presented scheme is useful to diagnosis a BLDC motor.

## REFERENCES

[1] O. Moseler and R. Isermann, "Application of model-based fault detection to a brushless dc motor," *IEEE Trans. on Industrial Electronics*, vol. 47, no. 5, pp. 1015-1020, October 2000.

[2] R. Raza, "Smart networks for control," *IEEE Spectrum*, pp. 49-55, June 1994.

[3] H. Ishii and B. A. Francis, "Stabilization with control networks," *Proc. UKACC Control 2000.* Cambridge, UK.

[4] X. Qun, H.-Y. Zhang, J. Liu, and J. Yang, "Fault detection and diagnosis of permanent-magnet DC motor based on parameter estimation and neural network," *IEEE Trans. on Industrial Electronics*, vol. 47, no. 5, pp. 1021-1030, October 2000.

[5] O. Moseler and R. Isermann, "Model-based fault detection for a brushless DC motor using parameter estimation," *IECON*, pp. 1956-1960, 1998.

[6] O. Moseler, D. Juričić, A. Rakar, and N. Müller, "Model-based fault diagnosis of an actuator system driven by the brushless DC motor," *Proc. of the American Control Conference*, pp. 3779-3783, 1999.

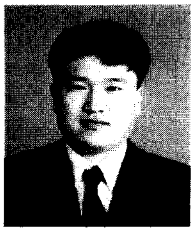
[7] S. H. Suh and K. J. Woo, "Observer based fault detection of PMSM using serial network," *Proc. of the 32nd ISR*, pp. 222-226, 2001.

[8] S.-H. Suh, J.-B. You and K.-J. Woo, "Parameter-estimation fault detection of BLDC motor using serial communication," *Journal of the Korean Institute of Illuminating and Electrical Installation Engineers*, vol. 16, no. 5, pp. 45-52, September 2002.

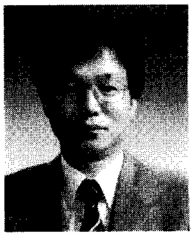
[9] L. Ljung, *System Identification Theory for the User*, Prentice-Hall, 1999.

[10] Ole Nørretranders, *Fault Diagnosis Using Parameter Estimation and Supervised Classification Techniques*, Intelligent Systems Laboratory Heriot-Watt University 1997.

[11] R. O. Duda, P. E. Hart, D. G. Stork, *Pattern Classification*, John Wiley & Sons, Inc., 2001.



**Suhk-Hoon Suh** received his B.S., M.S., and Ph. D. degrees in Electronic Engineering from Dankook University in 1990, 1992, and 2003, respectively. His research interests include control network application, embedded real-time system, and digital set-top box.



**Kwang-Joon Woo** received the B.S. and M.S. degrees in Electronic Engineering from Hanyang University in 1974 and 1977, the D.E.A. from the University de Strasbourg 1 in 1980, and the Ph.D. degree from Institut National Polytechnique de Grenoble in 1983. He is currently a Professor in the Department of Electronic Engineering, Dankook University.