Performance Evaluation of SANQ System Identification as a Fault Diagnosis Method Under a Stochastic Situation

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Abstract

We have constructed a failure diagnosis system using a quick identification method named as SANQ system identification [1], and verified the effectiveness and performance under the deterministic situation. However when the application of this method is considered, it is necessary to investigate the performance under the stochastic situation caused by, e.g. disturbances and measurement noises.

In this paper, we will verify characteristics and tolerance of the SANQ method under a stochastic situation, through simulation studies for a ship propulsion system. And we will try to modify the algorithm of the SANQ method so as to improve its performance under such a situation.

1 Introduction

It is important issue in maintenance engineering to construct a practical failure diagnosis system. There are various approaches for fault diagnosis [2], and identification-based fault diagnosis method is one of them. The most of faults in dynamic systems can be modeled as unexpected fluctuation of system parameters. Therefore, such faults can be detected and isolated by monitoring of the parameters as fault factors.

We have constructed a failure diagnosis system using a quick identification method, which is named as "SANQ (Simulator based Approach to Neat and Quick)" system identification. This identification method can accommodate various types of nonlinear systems described in state-space form. We have applied this method to a ship governor model and a ship-propulsion system model, and verified the effectiveness and performance for the fault diagnosis under the deterministic situation.

However, when considering practical application of this method, it is necessary to investigate the performance and characteristics under the stochastic situation. As the stochastic factors, disturbances in system dynamics and measurement noises in sensors are considered.

In this paper, we will verify the performance and characteristics of the diagnosis method under a stochastic situation caused by measurement noises, through simulation studies for a ship propulsion system [3]. And we

will try to modify the algorithm of the SANQ method to improve its performance under such situation.

2 SANQ System Identification Method

In this section, we will outline the basic formula of the SANQ system identification method.

In this method, let us consider continuous-time nonlinear systems whose dynamics can be expressed by the state-space form as a physical model. Such systems are described by non-linear dynamic and measurement equations,

$$\frac{d}{dt}x_p(t) = F(x_p(t), u_p(t), w(t), t; \theta_p) \quad (1)$$

$$z_p(t; \theta_p) = M(x_p(t), u_p(t), v(t), t; \theta_p) \quad (2)$$

where, $x_p(t)$ is the state variable, $z_p(t; \theta_p)$ the output variable measured by sensors, $u_p(t)$ the input signal, $w(t)$ the disturbance imposed on plant dynamics. $v(t)$ is measurement noise, and θ_p denotes the plant parameter.

In the SANQ identification method, it is assumed that a simulator with the same structure as that of the plant dynamics can be prepared. Then the simulator is constructed by

$$\frac{d}{dt}x_s(t) = F(x_s(t), u_p(t), t; \theta_s) \quad (3)$$

$$z_s(t; \theta_s) = M(x_s(t), u_p(t), t; \theta_s) \quad (4)$$

where $x_s(t)$ is the simulator state variable, $z_s(t; \theta_s)$ the output of the simulator, and $\theta = s$ denotes simulator parameter. Note that stochastic variables $w(t)$ and $v(t)$ are excluded from $F(\cdot)$ and $M(\cdot)$ in (1),(2). Thus the simulator dynamics are deterministic one.

In the SANQ method, the concept is based on an idea such that the simulator parameter is adjusted by successive perturbation procedure so as to minimize the output error between plant and simulator in the identification interval $[t_0 \ t_0 + T]$ (See Fig.1). The initial states

Fig.1 SANQ system identification

of simulator are included as adjustable parameters just like the simulator parameter vector to be adjusted and it consists of θ_p and $x_s(t_0)$.

The criterion function based on this concept is given by,

$$J_k(\theta) = \int_{t_0}^{t_0+T} \|z_p(t; \theta_p) - z_s(t; \theta_s)\|_R^2 dt \quad (5)$$

R is the weighting matrix which is appropriately selected by considering statistics of measurement noises, e.g. covariance matrix. So far, in the deterministic case, weighting matrix R have not been considered.

From the criterion function, we have the following estimation algorithm,

$$\begin{aligned} \hat{\delta\theta}_s(k+1) = & \left\{ \int_{t_0}^{t_0+T} \frac{\partial z_s^T(t; \hat{\theta}_s(k))}{\partial \theta} \cdot R \cdot \frac{\partial z_s(t; \hat{\theta}_s(k))}{\partial \theta^T} dt \right\}^{-1} \\ & \int_{t_0}^{t_0+T} \frac{\partial z_s^T(t; \hat{\theta}_s(k))}{\partial \theta} \cdot R \cdot \{z_p(t; \theta_p) - z_s(t; \hat{\theta}_s(k))\} dt \end{aligned} \quad (6)$$

$$\begin{aligned} \hat{\theta}_s(k+1) &= \hat{\theta}_s(k) + \hat{\delta\theta}_s(k) \\ k &= 1, 2, \dots \end{aligned} \quad (7)$$

where, $\partial z_s(t; \hat{\theta}_s(k))/\partial \theta_s$ in (6) is a sort of parameter sensitivity of the simulator output, and subjects to a differential equation derived from the simulator dynamics (3),(4). Thus, we can estimate the plant parameter θ_p together with the plant initial state $x_p(t_0)$ from adjusted simulator parameter $\hat{\theta}_s(k)$, where k denotes iteration number.

The criterion (5) seems to be a standard one for the output error type of identification. However, the

identification interval T can be taken to be a short interval comparable with the duration time of transient response, because the initial states $x_s(t_0)$ are included as adjustable parameters in this method. Therefore, the SANQ method makes it possible to execute a quick identification by using short time record of input-output data.

In this method, the identifiability is equivalent to existence of the inverse matrix in (6), that means independentness of $\frac{\partial}{\partial \theta} z_s(t; \theta_s)$ over the identification interval $[t_0, t_0 + T]$.

3 Decentralized Failure Diagnosis System

As is mentioned, the SANQ method contains state variables as adjustable parameters. Therefore, for plant with high dimension, the number of parameters to be estimated inevitably increases. Due to the fact, there may be considered the case that the identifiability isn't satisfied, or cost of calculation increases. To solve these problems, we construct "A Decentralized Failure Diagnosis System" as shown in Fig2.

Fig.2 Decentralized failure diagnosis system

The procedure of a decentralized failure diagnosis system is as follows:

First, a model with the same structure as that of plant dynamics is prepared for a simulator, and a fault is detected by comparing the outputs of the plant and the simulator. When a fault caused by unexpected change

of plant parameters has occurred, the effect will appear in the plant output. Therefore, it is possible to detect a fault from the output error between the plant and the simulator.

Then, after the fault detection, input and output data generated from the plant and the simulator are delivered to each decentralized simulator. Parameters which may be fault factor are estimated by using SANQ system identification method in each decentralized simulator.

Next, the fault factor is decided from the output error between the plant and each decentralized simulator as the result of estimation. Finally, in order to evaluate the fault degree, parameter set is estimated based on the identification results in decentralized simulators.

4 Ship-Propulsion System

In this section, as the plant to be diagnosed, we will consider a ship-propulsion system, which has one engine and one propeller. This system-model has been proposed for benchmark test of fault tolerant control by Izadi-Zamanabadi, M. Blanke et al, and is the model for a low speed marine vehicle.

Fig.3 Schematic diagram of the ship speed propulsion system

4.1 An overview of the ship-propulsion system

This system has following several features.

- The model of a small container ship. (length:147.2m, displacement:12,840m³)
- Various non-linearities are faithfully modeled.
- Six ordered non-linear system which has two inputs and four outputs.
- Various stochastic factors are modeled. (measurement noise, external force etc...)

The schematic diagram of this system is shown in Fig.3. Main components/subsystems of the system are:

- Propeller pitch control system.
- Governor.
- Diesel engine.
- Propeller characteristics.
- Ship speed dynamics.

This system has two inputs and four measurable outputs (See Fig.3). Inputs and outputs are following

- inputs
 - the shaft speed reference: n_{ref}
 - the propeller pitch reference: θ_{ref}
- outputs
 - the diesel engine shaft speed: n_m
 - propeller pitch position: θ_m
 - the fuel index: Y
 - the ship speed: U_m

4.2 Structure of the non-linear plant model

Each subsystems is thoroughly described in the following.

• Propeller pitch control system

The propeller pitch system is approximated by a simple integrator, and the system is controlled by a P-controller, and is described by following equations:

$$\begin{aligned}\theta_m &= \theta + \nu_\theta + \Delta\theta \\ u_\theta &= k_t(\theta_{ref} - \theta_m) \\ \dot{\theta} &= \max(\dot{\theta}_{min}, \min(u_\theta, \dot{\theta}_{max})) + \Delta\dot{\theta}_{inc} \\ \theta &= \max(\theta_{min}, \min(\theta, \theta_{max}))\end{aligned}\quad (8)$$

where θ_m is the measured propeller pitch, $(\dot{\theta}_{max}, \dot{\theta}_{min})$ are the limits set by the hydraulic pump, and $(\theta_{max}, \theta_{min})$ are the physical limits for propeller. ν_θ is the measurement noise. The available signals are θ and θ_{ref} .

• Governor

Governor mainly consists of a PI-controller. Input to the Governor is the difference between shaft speed reference n_{ref} and measured shaft speed n_m . The output is the fuel Index Y . An anti-windup arrangement is included in the Governor.

$$\begin{aligned}n_m &= n + \nu_n + \Delta n \\ \dot{Y}_i &= \frac{k_r}{\tau_i}((n_{ref} - n_m) - K(Y_{PI} - Y_{PIb})) \\ Y_{PIb} &= Y_i + k_r((n_{ref} - n_m)) \\ Y_{PI} &= \min(\max(Y_{PIb}, Y_{lb}), Y_{ub})\end{aligned}\quad (9)$$

Due to physical constraints, the fuel index generated by governor is modified by,

$$y_{max} = \begin{cases} 1 & \text{if } n_m \geq 0.8n_{max,a}, \\ \frac{1.5}{n_{max,a}}n_m - 0.2 & \text{if } 0.4n_{max,a} < n_m < 0.8n_{max,a}, \\ 0.4 & \text{if } n_m \leq 0.4n_{max,a} \end{cases}$$

$$Y = \max(0, \min(Y_{PI}, y_{max})) \quad (10)$$

• Diesel Engine Dynamics

According to the fuel index, the diesel engine generate a torque, Q_{eng} . The relation between generated torque and fuel index is described by following equation:

$$\frac{Q_{eng}}{Y}(s) = \frac{(k_y + \Delta k_y)e^{-\tau s}}{1 + \tau_c s} \quad (11)$$

Then the torque turns the shaft. When considering the applied torques to the shaft, following differential equation is given:

$$I_m \dot{n} = Q_{eng} - Q_{prop} - Q_f \quad (12)$$

$Q_{eng}[\text{Nm}]$ is the torque developed by diesel engine, $Q_{prop}[\text{Nm}]$ is the developed torque from propeller dynamics, and $Q_f[\text{Nm}]$ is the friction torque.

• Propeller Characteristics

The propeller pitch is the angle between a single propeller blade and its turning direction. The developed propeller thrust and propeller torque are determined by following bilinear relation:

$$T_{prop} = T_{|n|n}(\theta)|n|n + T_{|n|V_a}(\theta)|n|V_a \quad (13)$$

$$Q_{prop} = Q_{0|n|n} + Q_{|n|n}(\theta)|n|n + Q_{|n|V_a}(\theta)|n|V_a \quad (14)$$

where $V_a[\text{m/s}]$ is the velocity of the water that goes into the propeller disc and $n[\text{rad/s}]$ is the shaft speed. Q_0 denotes the torque which is produced by the propeller when the pitch is zero.

The coefficients $T_{|n|n}$, $T_{|n|V_a}$, $Q_{|n|n}$, $Q_{|n|V_a}$ are complex functions of the pitch angle θ .

• Ship Speed Dynamics

The ship speed dynamics is described by:

$$(m - X_{\dot{U}})\dot{U} = R(U) + (1 - t)T_{prop} - T_{ext} \quad (15)$$

$$U_m = U + \nu_U \quad (16)$$

$R(U)$ describes the resistance of the ship in the water and is negative quantity. $X_{\dot{U}}$ represents the added mass in surge and is a negative quantity. T_{ext} represents the external force imposed on the ship motion by wind and waves. U_m is the measured ship velocity and ν_m is the measurement noise.

The following variables are included as stochastic factors in this system.

- measurement noise: $\nu_\theta, \nu_n, \nu_U, \nu_Y$
- the velocity of the water which goes into the propeller disc: V_a
- the external force imposed on the ship motion: T_{ext}

5 Simulation Studies under a Stochastic Situation

Simulation studies on paramter identification and fault diagnosis of the ship propulsion system have been carried out.

As is mentioned, so far, the effectiveness and performance of the SANQ method for fault diagnosis have been verified under the deterministic situation. In this section, the performance of this method is verified under a stochastic situation only caused by measurement noises. On the other hand, the stochastic factors in dynamics equation are left to be future studies.

• Specifications

Each output is measured with additive noise. The noise is assumed to be a normal distributed white Gaussian noise with zero mean. Standard deviations of the noises for outputs used in the simulation are given in Table 1.

Table 1: standard deviation of noise for each output

Signal	Name	Standard deviation
U	ship speed	$0.01 * U_{max}(= 9.7[\text{m/s}])$
n	shaft speed	$0.005 * n_{max}(= 12.5[\text{rad/s}])$
θ	pitch angle	$0.425 * \theta_{max}(= 1)$
Y	fuel index	$0.005 * Y_{max}(= 1)$

We select three parameters as fault factors in the ship-propulsion system (Table 2), and identify them using the SANQ method when each parameter change has occurred individually.

Table 2: parameters as fault factor

par.	description	value	unit
k_y	engine gain	1.137×10^6	
I_m	inertia	0.25×10^6	kgm^2
k_t	pitch angle control gain	0.15	

Further, assuming the independence of each noise, we will select weighting matrix R to be diagonal matrix. Its factors are variances of measurement noises in outputs,

$$R = \begin{bmatrix} \text{cov}(\nu_n) & 0 & 0 & 0 \\ 0 & \text{cov}(\nu_\theta) & 0 & 0 \\ 0 & 0 & \text{cov}(\nu_U) & 0 \\ 0 & 0 & 0 & \text{cov}(\nu_Y) \end{bmatrix}^{-1} \quad (17)$$

The fault modes are specified by following three cases:

1. The change of k_y .
2. The change of I_m .
3. The change of k_t .

The other specifications are considered as follows and they are explained in Fig.4.

- data interval for simulation: $[0 \sim 3500]sec$
- the time when the parameter was changed: at $500sec$
- the degree of paramter change: $+10\%$
- identification interval: $T = 60[step] (= 60sec)$
- iteration number of the SANQ method: $20times$

Fig.4 Specification of simulation studies

5.1 Simulation results

The simulation results are shown in Fig.5 for the case 1, in Fig.6 for the case 2, in Fig.7 for the case 3, while Fig.8 ~ Fig.10 show the results without a weighting matrix R in the SANQ method. In each case, estimated values of plant parameters as the fault factors and their true values are plotted.

The estimation errors are evaluated by normalized values in Table 3 and Table 4, where ϵ_1 denotes estimation errors with weighting matrix R , and ϵ_2 denotes those without R .

Table 3: estimation error for initial estimates

	case 1(k_y)	case 2(I_m)	case 3(k_t)
ϵ_1	0.08061	0.02530	0.09234
ϵ_2	0.13602	0.17623	0.13429

Table 4: estimation error for parameters

	case 1(k_y)	case 2(I_m)	case 3(k_t)
ϵ_1	0.00118	0.00062	0.00637
ϵ_2	0.00243	0.00455	0.00188

Fig.5 Simulation result (weighted)
case 1: change of k_y

Fig.6 Simulation result (weighted)
case 2: change of I_m

Fig.7 Simulation result (weighted)
case 3: change of k_t

Fig.8 Simulation result (no-weighted)
case 1: change of k_y

Fig.9 Simulation result (no-weighted)
case 2: change of I_m

Fig.10 Simulation result (no-weighted)
case 3: change of k_t

5.2 Discussions

From Fig.8 ~ Fig.10, we can see that some degree of bias is appeared in each estimated result in the case without weighting matrix R . On the other hand, in the case with weighting matrix, it can be seen that the effect of bias is suppressed (See Fig.5 ~ Fig.6).

It can be seen from Table 3 and Table 4 that a reasonable estimation accuracy is obtained.

Therefore, when a system has a stochastic factor like a measurement noise, appropriate weighting matrix can be one of solutions to suppress its effects.

6 Conclusions

In order to examine the performance of the SANQ method under a stochastic situation like a measurement noise, we have carried out simulation studies on identification and fault diagnosis of the ship propulsion system.

As the result, it has been confirmed that the noises degrade the performance of the SANQ method. However it can be seen that the effects are suppressed by introducing an appropriate weighting matrix into the criterion function. Therefore, to guarantee the performance of this method under the situation, it is important to select an 'optimal' weighting matrix. On this concern, we need more case studies, and it is important to develop another approach to this problem, too. The verification for other stochastic factors is still open problem to be investigated.

References

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