ANALYSIS OF SYSTEM RELIABILITY BASED ON FAULT TOLERANT CONTROL AND USING VIBROACOUSTIC PARAMETER

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Abstract: *The paper presents possibility of fault detection and isolation in rotation machinery using analytical redundancy. It outlines the most important techniques of model-based residual generation using parameter identification and state estimation methods with emphasis the problems of reliability. A solution to the fundamental problem of fault detection providing the maximum achievable effectiveness by using condition-based maintenance system, reducing downtime, decreasing maintenance cost, and increasing machine availability is given. With the aim of synthesizing and providing the information of researcher`s community, this paper attempts to summarize and classify the recent published techniques in diagnosis and prognosis of rotating machinery. Furthermore, it also discusses the opportunities as well as the challenges for conducting advance research in the field of remain useful life prognosis.*

The results are very important for robust instrument fault detection, component fault detection and actuator fault detection. Finally we discuss the approach of fault diagnosis using a combination of analytical and knowledge-based redundancy.

Keywords: AGRICULTURE ROBOT, SYSTEM RELIABILITY, FAULT TOLERANT CONTROL

1. Introduction

The detection and diagnosis of faults in semi-public agricultural unmanned machines is one of the most important tasks assigned to the autonomous operation. The early indication of incipient failures can help avoid major machine breakdowns , that could result in substantial material damage. Recently, technical diagnostic systems have been applied to such equipment as automobiles and mobile robots. **A** model-based method was used to check the operation of gearboxes, but the information represented by multiple interrelated machinery measurements was not applied. The literature of process fault diagnosis is not very extensive, especially when compared to the control engineering. We will consider three classes of failures presented by Gertler [1]:

- *Additive measurement faults.* These are discrepancies between the measured and true values of output or input variables, like sensor biases or actuator malfunctions of actuator.
- *Additive process faults.* These are disturbances (unmeasured inputs) acting on the machine, which are normally zero and cause a shift in the object outputs independent of the measured inputs.
- *Multiplicative process faults.* These are connecting with changes (abrupt or gradual) of the machine parameters. Such faults best describe the deterioration of components.

2. Fault tolerant systems

Most model-based failure detection and isolation methods rely on the idea of *analytical redundancy* [2]. It means that sensory measurements are compared to analytically obtained values of the respective variable and this deference are called residuals. Depending on utilizing redundancy fault tolerant control systems can be consider as two different types: passive and active. In case of passive one potential failures of systems component are assumed to be known a priori and this very can be taken as possible and are analysing. The control system can tolerate a faults without any modification. Unfortunately the passive system can not perform in proper way when an unexpected failures occur. On the other sidle the active fault tolerant control systems can be reconfigured when unexpected fault occurs. Such approach is possible when fault detection and identification procedures are performers in the real-time. The deviation of residuals from zero is the combined result of noise and faults. With any significant noise present, statistical analysis (statistical testing) is necessary.

In the most case study the failure detection and identification methods rely on linear dynamic models. As is consider in an open-loop system can be divided into subsystems like actuators, system dynamics and sensors and can be described by the state-space model as follow;

$$\dot{x}(t) = Ax(t) + B\big(u(t) + f_a(t)\big) \tag{1}$$

$$y_f(t) = Cx(t) + D(u(t) + f_a(x) \tag{2}$$

where, x(t) – state vector
A, B, C, D – matrices of proper dimensions
u(t), y(t) – input vector and output vector signals
$y_t(t)$ –output corrupted by actuator and sensor faults
$f_a(t)$ – actuator fault, $f_s(t)$ – sensor fault

The model – based failure detection and identification is the open-loop although one considers that the system is in the control loop, hence it is not necessary to consider the controller in fault diagnosis procedure.

As we shown before, faults are detected by using a threshold on a residual generated from difference between real measurements models. In other approach the detecting on faults is made on the base of limit checking: comparison process variables with present limits. The residual signals represent the inconsistency between the actual system a variables and the mathematical model. The traditional approach to residual generation is the use of duplication of the system. The disadvantage of this method is the nessesity of stability investigation.

When a residual signal is established we need to calculate the difference between the particular fault and others.

It should be noted that most failure detection and isolation methods do utilize the relation value of residuals to the test thresholds.

The information embodied in the size of the residuals beyond their relation to test thresholds (Fig.1).

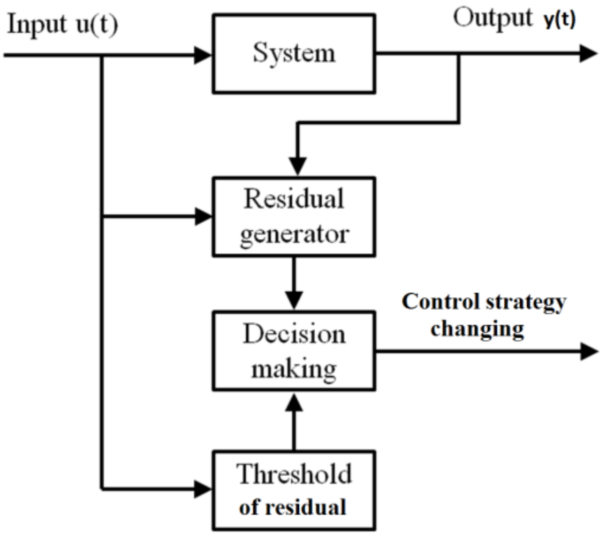

Fig. 1 *Failure tolerant system with use of residual threshold.*

Assume that the fault is detected at the time instant t_f, then the following modified command input $\mathbf{u_f}$ will be generated based on the designed command inputs $\mathbf{u_n}$ as

$$u'_t = u_{t-\Delta t} + \varkappa_t (u'_t - u'_{t-\Delta t}) \tag{3}$$

where

$$u'_t = \begin{cases} u, t < t_f \\ u_f, t \geq t_f \end{cases}$$

and $\varkappa_t \in (0,1)$

is a weighting parameter chosen to satisfy the actuator constraints.

To provide smooth switching between u_n and u_f the following variable weighting parameter can be used:

$$\varkappa_t = 1 - \delta e^{-\tau(t-t_f)}, \tau \geq t_f \tag{4}$$

where $\tau > 0$ and $\delta > 0$ are two design parameters.. It is important to note that the degraded performance at the steady-state is achieved by the modified command input u_f. The selection of the parameter $\varkappa_t$ can also be carried out by using optimization-based techniques [3, 7].

The concept of reconfigurability was introduced by [8], as control system quality under given faulty conditions. LTI system reconfigurability can be also evaluated using the controllability and observability Gramians [9]. In the work of Staroswiecki [10], performance-based control reconfigurability is evaluated as the ability of the system considered to keep or recover some admissible performances when a fault occurs.

3. Use of proportional hazards models.

As presented previously, reconfigurability based on the controllability Gramian is applied to evaluate the system performances, which can be achieved by a fault-tolerant control scheme. To improve system dependability, it is crucial to ensure that the reconfigured system can provide reliability of system achieve the control objective until the end of the mission.

In this study, a Weibull,s distribution is considered as model reliability. In fact, reliability evolution is characterized by a given failure rate. Thus, failure rates are obtained from components under different levels of degradation. Several mathematical models have been developed to define the failure function in order to estimate the failure rate λ [11]. Among them, the proportional hazard model introduced by Cox [12] is used in this paper.

The failure rate is modeled PHM approach:

As has been presented in paper [13], the use of Proportional Hazards Model creates an opportunity for examining the influence of systemic variables (e.g. temperature, pressure, load, etc.) on the system's reliability.

The assumptions of the Proportional Hazards Model:

1. The ratio of intensity of damage for two different values of a systemic variable is independent of time
2. Intensity of defects for various values of the systemic variable are described by this distribution,

Based on the above assumptions we can write the following equation:

$$\lambda(t,z,\beta) = \lambda_0(t)\, r(z,\beta) \tag{5}$$

where:

t – time

z – systemic variable

β - unknown parameter accounting for the influence of the systemic variable

$\lambda_0(t)$ – intensity of defects for the value of the systemic variable adopted as the reference level

If we assume, according to Cox model (1972), that:

$$r(z,\beta) = e^{z\beta} \tag{6}$$

we obtain:

$$\lambda(t,z,\beta) = \lambda_0(t)\, e^{z\beta} \tag{7}$$

The model that could be expressed by means of equation (1) is called the Proportional Hazards Model and we can generalize it to cover any number of systemic variables:

$$\begin{aligned}\lambda(t, z_1,...z_n, \beta_1,..., \beta_n) &= \\ &= \lambda_0(t)\, r(z_1,...z_n, \beta_1,..., \beta_n)\end{aligned} \tag{8}$$

after incorporating the Cox model we will get:

$$\lambda(t, z_1,...z_n, \beta_1,..., \beta_n) = \lambda_0(t)\, e^{z_1\beta_1 + ... + z_n\beta_n} \tag{9}$$

The exponential form of function *r(z,β)* guarantees that the intensity function assumes non-negative values irrespective of the value of coefficients.

The distribution used most frequently when analyzing reliability is the exponential distribution for which the intensity of defects is constant and thus also the relationship of intensity for two groups of data related to defined defects will also be constant, which meets the requirements of the Proportional Hazards Model. Assuming exponential distribution, we rule out the possibility of accounting for influence of time. For that reason we should consider the possibility of using Weibull distribution, and thus let us analyze the conditions that must be fulfilled by the distribution's parameters to meet the requirements of a Proportional Hazards Model. The intensity of defects for Weibull distribution has the following form:

$$\lambda = \frac{\alpha}{\eta^{\alpha}} t^{\alpha - 1} \tag{10}$$

while the relation of intensity is:

$$\frac{\lambda_1}{\lambda_2} = \frac{\dfrac{\alpha_1}{\eta_1^{\alpha_1}} t^{\alpha_1 - 1}}{\dfrac{\alpha_2}{\eta_2^{\alpha_2}} t^{\alpha_2 - 1}} = \frac{\alpha_1}{\alpha_2} \cdot \frac{\eta_2^{\alpha_2}}{\eta_1^{\alpha_1}} \cdot \frac{t^{\alpha_1 - 1}}{t^{\alpha_2 - 1}} \tag{11}$$

The above relationship shows that the assumptions of the Proportional Hazards Model will be fulfilled for Weinbull's model only if the coefficient of shape stays constant for both groups of data.

4. Reliability evaluation [14]

Thus, actuator reliability can be evaluated as follows control effectiveness (2). Then the system dynamics can be expressed by

$$\dot{y} = C\dot{x} = CAx + CBu_f \;. \tag{12}$$

At the current state $x(t)$, suppose that the reference baseline system control law for the desired behaviour would produce input u_n if all of the control actuators were healthy. Then the desired rate of the controlled output would be

$$\dot{y}_n = C\dot{x} = CAx + CBu_n. \quad (13)$$

FTC seeks an input control u that makes the right-hand side of (12) as close as possible to that of (13), that is,

$$Bu_n = Bu_f, \quad (14)$$

where, consequently, y will remain close to y_n for

$$u = (I - \Gamma)-1u_n. \quad (15)$$

Therefore, based on (6) and (16), the failure rate and the reliability of the actuator under degraded functional conditions can be established according to the loss of effectiveness factors γ_i and u_{in} as follows:

$$\lambda i(\gamma) = \lambda 0ie(1-\gamma i)-1\alpha u_{in}, \quad (16)$$

$$Ri(t,\gamma) = exp^{-(\lambda t)^{\alpha}}$$
(17)

The overall system reliability depends on the way in which their components and subsystems are connected.

4. Conclusions

The main features of model-based failure detection and isolation methods have been surveyed in this paper. Several techniques to generate residuals from plant measurements and to obtain failure signatures of the residuals have been discussed.

It has been pointed out that the major quality issues of failure detection and identification algorithms are sensitivity, and robustness. Defectivity is related primarily to the structure of the residual-generating model and can be achieved by appropriate model transformation. Sensitivity and **ro**bustness requirements are taken into consideration in a design framework that makes use of the analytical redundancy. The results described in the paper show that analysis can be established by using system reliability evaluation in addition to the vibroacoustics parameter od degradation.

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