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Fault prediction of the nonlinear systems with uncertainty

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ABSTRACT

Fault prediction which can forecast the fault in advance to avoid large calamity has attracted more and more attention. However, the current filter based fault prediction methods for the nonlinear systems are all based on the framework of the probability theory, and cannot realize fault prediction of the nonlinear systems with fuzzy uncertainty. Based on the extended fuzzy Kalman filter (EFKF) and the extended orthogonality principle, an improved fuzzy Kalman filter (IFKF) is firstly proposed to estimate the system states or the parameters in this paper. Then, according to the IFKF, a multi-step improved fuzzy Kalman predictor (MIFKP), which can be considered as an adaptive predictor, is obtained. Once the characteristic parameter is chosen, the MIFKP can be used to implement the multi-step fault prediction. Simulation results demonstrate that the proposed approach has the better prediction ability and stronger robustness than the traditional multi-step extended fuzzy Kalman predictor (MEFKP).

1. Introduction

Fault prediction mainly deals with the fault that will happen according to the past and current states of the systems, which can avoid large calamity. Therefore, with the growing demand for higher operational efficiency and safety in industrial systems, fault prediction has attracted considerable attention world-widely, especially in some systems such as nuclear power station and missile control loop which need high security and reliability.

Saeks et al. began research of the fault prediction in 1979 [1]. Because the fault symptoms which are studied in fault prediction are so small that they have not destroyed the system, it is difficult to identify the symptoms, and the development of these techniques is very slow.

The current filter based fault prediction methods of nonlinear systems mainly include the extended Kalman predictor and the strong tracking predictor for nonlinear and Gaussian system [2], and particle predictor for nonlinear and non-Gaussian system [3]. The main idea of these methods is: based on transformations of the current filters, the forecasting models can be established and are used to forecast the future states or parameters which are compared with the given threshold to determine the future fault. The filter based methods are all based on the framework of the probability.

However, there exist a lot of nonlinear systems with fuzzy uncertainty in engineering. For example, due to the drift of the sensors, the measurement is uncertain and the distribution of the noise is not symmetric. In addition, due to the influence of outside uncertainty, there also exists uncertainty in the input. Obviously, the current methods cannot implement fault prediction for these systems.

In order to deal with the fuzzy uncertainty, the extended fuzzy Kalman filter (EFKF) proposed by Matia et al. is more appropriate to deal with the state or parameter estimation of the fuzzily uncertain systems [4]. The characteristics of this

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method are as follows. Firstly, replacing Gaussian distribution by the trapezoidal distributions allows the introduction of asymmetries in a natural manner. Secondly, propagating the main points of a trapezoidal distribution through the nonlinear models, and recalculating its center of gravity and uncertainty of propagation, will produce less error than propagating the mean value and the variance of the Gaussian distribution through a linearized model. Finally but by no means least importantly, instead of trying to build very accurate models by understanding the available knowledge, the knowledge is kept in its qualitative form, which is very helpful to interpret the results. On the other hand, several fuzzy Kalman methods which are all based on the Takagi–Sugeno (T–S) model have been proposed [5–12]. In these methods, equipped with the ability of the fuzzy logic to approximate the nonlinear systems, the Kalman filter can well estimate the states or the parameters of the nonlinear systems. However, they are only applicable to the cases where there exists the probabilistic uncertainty.

Though the EFKF can deal with the fuzzy uncertainty, it cannot realize the prediction and also is inapplicable to the cases where there exist the model mismatches in the nonlinear systems. Fortunately, using the orthogonality principle and the extended Kalman filter (EKF), Wang et al. have proposed the strong tracking predictor (STP), which has the strong robustness to the model mismatches [13]. However, the STP is also on the basis of the probabilistic theory and cannot deal with the fuzzy uncertainty. Therefore, based on the EFKF and the extended orthogonality principle, a new multi-step fault prediction method is proposed for the nonlinear systems in this paper.

This paper is organized as follows. In Section 2, some preliminaries about the possibility distribution and fault prediction are briefly reviewed. The original EFKF of the nonlinear systems is presented in Section 3. Based on the extended orthogonality principle, an improved fuzzy Kalman filter (IFKF) of the nonlinear systems is proposed in Section 4. Moreover, a multi-step fault prediction algorithm is also given. The effectiveness of the proposed fault prediction algorithm is demonstrated in Section 5. Finally, Section 6 draws our conclusions.

2. Preliminaries

2.1. Fuzzy variable and uncertainty management

A fuzzy variable p is defined over the universe of discourse P, using a trapezoidal possibility distribution $\pi_P(p)$ given by

$$\pi_P(p) = \begin{cases} 1 & \forall p \in [p_2, p_3] \\ 0 & \forall p \notin [p_1, p_4] \end{cases} \tag{1}$$

The meaning of $\pi_P(p)$ is shown in Fig. 1.

Eqs. (2)–(5) are defined as the expectation, the area of the distribution, the center of gravity and the uncertainty of the distribution, respectively [4].

$$E\{p\} \sim \Pi(p_1, p_2, p_3, p_4) \tag{2}$$

$$\chi_p = \int \pi_P(p)\mathrm{d}p \tag{3}$$

$$\tilde{p} = C\{p\} = \frac{\int p\pi_P(p)\mathrm{d}p}{\chi_p} \tag{4}$$

$$U\{p\} = C\left\{(p-\tilde{p})^2\right\} = \frac{\int (p-\tilde{p})^2 \pi_P(p)\mathrm{d}p}{\chi_p} \tag{5}$$

In the case of a multivariable system, with p and q defined over the universes of discourse P and Q, respectively, a joint possibility distribution $\pi_{P,Q}(p, q)$ is used. Then there are following definitions [4].

$$\tilde{p} = C\{p\} = \frac{\int\int p\pi_{P,Q}(p,q)\mathrm{d}p\mathrm{d}q}{\chi_{p,q}} = \frac{\int p \int \pi_{P,Q}(p,q)\mathrm{d}p\mathrm{d}q}{\chi_{p,q}} = \frac{\int p\pi_P(p)\mathrm{d}p}{\chi_p} \tag{6}$$

$$\tilde{q} = C\{q\} = \frac{\int\int q\pi_{P,Q}(p,q)\mathrm{d}p\mathrm{d}q}{\chi_{p,q}} = \frac{\int q \int \pi_{P,Q}(p,q)\mathrm{d}p\mathrm{d}q}{\chi_{p,q}} = \frac{\int q\pi_Q(q)\mathrm{d}q}{\chi_q} \tag{7}$$

$$Dep\{p,q\} = C\{(p-\tilde{p})(q-\tilde{q})\} = \frac{\int\int (p-\tilde{p})(q-\tilde{q})\pi_{P,Q}(p,q)\mathrm{d}p\mathrm{d}q}{\chi_{p,q}} \tag{8}$$

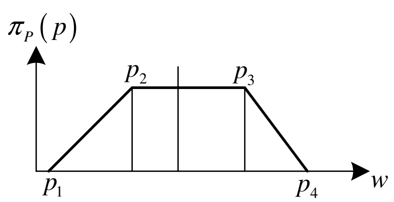

Fig. 1. Possibility distribution.