Model-Based Diagnosis of Chaotic Vibration Signals

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Abstract:

This paper presents a model-based approach to on-line monitoring and fault diagnosis of rotating machinery. Fault (e.g., Rub, Imbalance) modes of rotating machines are classified using nonlinear dynamic models with quasi-periodic and chaotic behavior. The paper identifies a class of fault scenarios under which the well-accepted nonlinear state filters (e.g., EKF) can not be used to monitor or diagnose the machinery. An effective on-line model-based monitoring and diagnosis algorithm is proposed. The algorithm is based on computationally efficient algorithms for signal processing and parameter identification.

1. Introduction

Rotating machines are important assets in many industries, in particular the power generation industry. Operational efficiency and maintenance costs are crucial design requirements that result in today's complex rotor dynamics, and hence the need for sophisticated health monitoring and diagnosis schemes.

There have been several empirical approaches to fault diagnosis of rotating machinery based on the analysis of vibration signals; including spectral analysis, orbit diagrams, complexity indices and more recently neural networks and fuzzy logic. Vibration signals pose a key challenge to classical signal processing due to the nonstationary nature of their spectrum. Recent digital signal processing algorithms such as fast wavelet transforms are considered as promising tools.

This paper outlines a model-based approach to fault diagnosis of rotating machines, see [1] for a recent survey on the topic.

In general, model-based approaches to fault diagnosis are based on the principle of analytical redundancy, which involves a residual analysis of a set of linear Kalman Filters [2]. Recently, stochastic nonlinear Filtering, based on nonlinear observers, has been recommended as an effective approach to diagnosis of rotating machines, [3], [8].

Unfortunately, in the case of complex rotor dynamics, (e.g., in case of rub impact behavior, [7], the vibration signal becomes chaotic with high complexity measures, e.g., Kolmogorov information index, Lyaponov exponent or fractal dimension), model-based techniques that are based on the principle of analytical redundancy and fault filters (EKF and nonlinear observers) are not suitable.

Specifically, vibration signals (and hence the position of the rotor) of complex rotor dynamics are not predictable because of the sensitivity of the orbits to initial conditions or what is called the "Butterfly effect". This implies that the residuals between the estimation errors of any state estimator are of the same order as the vibration signals themselves, [4].

An alternative model-based approach to diagnosis of nonlinear dynamics is based on parameter identification and pattern recognition. The approach has been successfully applied to electromechanical systems, in case of single faults, [5], and compound faults [6].

Unlike state estimators, parameter estimators are based on input-output models of the dynamics, rather than the state information. Furthermore, nonlinear rotor dynamic models that are linear in the parameter can result in efficient on-line fault diagnosis algorithms.

This paper outlines an on-line algorithm based on parameter estimation and pattern recognition. The proposed algorithm is presented in section 3. Applications to rotor-stator dynamic simulation are described in section 4. The rotor dynamic model used in the paper is described below, in section 2.

2. Rotor-Stator Rub Dynamics

To investigate the dynamics of rotor (or blade) casing systems during rub interaction, We adopted the mathematical model in [7] to study the forced chaotic dynamical behavior of rotating machines. Specifically, it accounts for the rub interaction between a rotor and a boundary with a nonlinear restoring force, figure.1. The proposed approach, is generic and can be applied to other models as well.

The associated pair of coupled nonlinear second order ODEs that represent the rub interaction behavior is then modeled in terms of deviations in the model parameters. Using Newton's Law and the model for Contact Forces (Hertzian):

$$M\,\ddot{\vec{r}}_m = M\left(\ddot{\vec{r}}_0 + \ddot{\vec{r}}_\beta\right) = \vec{G} + \vec{R} + \vec{F}_n \qquad (1)$$

M : rotor mass
$\vec{G}$: Gravity
$\vec{R}$: Linear restoring force (bearings)
$\vec{F}_n$: Nonlinear contact and rubbing forces
r_m : Relative position of the mass center w.r.t. stator's center
r_0 : Relative position of the rotor's center w.r.t. stator's center
r_β : Relative position of the mass center w.r.t. rotor's center

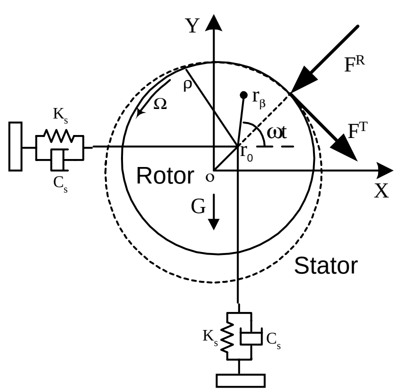

Figure 1. The rotor-stator interaction dynamics are modeled using a disk with 2-DOF within a circle.

The cross section of the rotor is modeled with two generalized coordinates. The disc translates in the X and Y directions and rotates around Z direction. The above equation can be scaled and simplified into the following ODE:

$$\ddot{X}+2\zeta\,\dot{X}+X=-\langle K_\beta\delta^\alpha(\cos\theta-\mu\sin\theta)\rangle+E\omega^2\cos\omega\tau \qquad (2)$$

$$\ddot{Y}+2\zeta\,\dot{Y}+Y=-\langle K_\beta\delta^\alpha(\sin\theta-\psi\mu\cos\theta)\rangle+E\omega^2\sin\omega\tau-G$$

where,

ξ : Dimensionless damping

K_β : Stiffness constant for Hertezian contact force

μ : Coefficient of Coulomb friction

E : Eccentrity ratio

G : Dimensionless gravity

α : Deformation exponent for Hertezian contact force $(1\le\alpha\le 2)$

ω : Dimensionless rotational speed

$\psi = sign$(velocity of rotor at impact point)

$<g(\delta)>=g(\delta)$ if $\delta>0$; otherwise 0.

The imbalance rub-impact faults are modeled as changes in the parameters $\xi, K_\beta, \mu, E,$ *and* G, which in turn cause the dynamic behavior of the state X and Y to change, moving from the one operating regime to another (linear, period doubling, quasi-periodic, or chaotic).

The impact of different types of faults on parameters, [7], is summarized in the following Table. Both the friction and damping coefficients have significant impact on the complexity of the dynamic behavior of the model. Figure 2 illustrates the time history and orbit diagram, along with its Pioncare' map of a simulation using [0.14,1.33E3,0.50,0.49,0.13].

Fault category	**Dynamic Mode**	**Sample Parameter Values**
Swinging with Chattering. Rotor rubbing with the bottom section of the clearance.	Harmonics-Order 1 Harmonics-Order 2 Chaotic	[0.20,1.61E4,0.13,0.40,1.58] [0.35,1.22E4,0.68,0.31,1.20] [0.20,1.25E4,0.13,0.31,1.23]
Rub impact causing wear around N points.	Harmonics Chaotic Harmonic	[0.16,1.25E4,0.30,0.75,.123] [0.032,1.00E4,0.1,0.80,.981] [0.14,1.33E4,0.30,0.45,.131]
Rub impact all around the clearance sector	Harmonics-Order 20 Chaotic Quasi-Periodic	[.024,1.389E4,.13,.347,.136] [.135,1.124E5,0.13,0.32,1.1] [0.14,1.33E3,0.50,0.49,0.13]

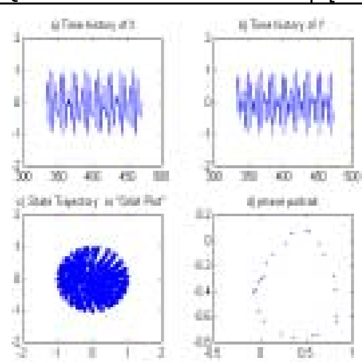

Figure 2. Time history, Orbit diagram and Poincare' map using [0.14,1.33E3,0.50,0.49,0.13].

3. Algorithm

The set of parameters $\xi, K_\beta, \mu, E, and\ G$ provides complete information about all modes of the rotor-stator system, including the normal and different fault modes. Therefore, if the parameters of the model can be accurately and recursively estimated from real-time vibration data, then the diagnosis task can be reduced to that of parameter estimation and parameter (pattern) classification.

For all practical purposes, the output map between the rotor position $[X(t), Y(t)]$ and the data from the vibration sensors is linear, and hence one can assume that map to be the identity map. Then, the nonlinear rotor-stator model can be represented in the following linear input-output model,

$$y(t) = \psi(t)\theta(t-1) + n(t) \qquad (3)$$

where,

$$y(t) = [X(t), Y(t)]'$$

$$\psi(t) = \begin{bmatrix} -2\dot{X} & -\langle \delta^\alpha \cos\theta \rangle & \langle \delta^\alpha \sin\theta \rangle & \omega^2 \cos\omega\tau & 0 & -\ddot{X} \\ -2\dot{Y} & -\langle \delta^\alpha \sin\theta \rangle & \langle \delta^\alpha \cos\theta \rangle & \omega^2 \sin\omega\tau & -1 & -\ddot{Y} \end{bmatrix}$$

$$\theta(t) = [\xi, K_\beta, \mu, E, G, 1]$$

A natural predictor of the vibration data $y(t)$ is then, $\hat{y}(t) = \psi^T(t)\theta(t-1)$ and a typical recursive estimation algorithm, [9], is

$$\hat{\theta}(t) = \hat{\theta}(t-1) + K(t)(y(t) - \hat{y}(t)) \qquad (4)$$

Here $\hat{\theta}(t)$ is the parameter estimate at time t, and y(t) is the observed 2-D vibration data at time t. The estimate $\hat{y}(t)$ is a prediction of the 2-D vibration data y(t) based on observations up to time (t-1), and the parameter estimate at time (t-1). The gain K(t) is the Kalman gain, it is typically chosen as $\mathrm{K(t) = Q(t)}\psi(t)$. Other efficient algorithms can also be applied, e.g., to provide unbiased estimates.

The elements of the $\psi(t)$ matrix can be obtained from the vibration data at time t using state-space filters. To avoid modeling the noise in the ARMAX model (3), a wavelet-based algorithm has been used to denoising the vibration signals before being fed to the parameter estimator.

The output of the parameter estimator is used to classify the vibration data using the nearest neighbor algorithm, Figure 3. However, in some practical applications, the impact of the noise and compound faults on the parameter estimate can lead to lower classification rate. In those cases, a Kolmogorov complexity-based classifier, [6], can be used.

4. Simulations

To test the proposed algorithm, simulation experiments for the model given by (1) have been conducted. The goal is to classify real-time vibration data into one of the fault categories and dynamic modes, as in Table 1. To demonstrate the performance of the diagnosis algorithm the rotor-stator process was simulated under different faults conditions, i.e., quasi-periodic and chaotic dynamics, signal to noise ratios and random initial conditions.

Abrupt changes in the values of the parameters were introduced every 100 seconds (2000 samples at 0.05 sampling rate). An additive sensor noise at SNR=90% and an additive process noise (periodic and rub impact components) were applied to the model. The response of the parameter estimator is displayed in Figure 4. The estimator was able to robustly track the parameters values in all cases.

Figure 5 (a), (b) and (c) show the orbit diagram for both the model (no noise), simulated data and the predictor, respectively, during the second segment of the experiment [2000,4000]. The predictor output correlates with the original except during the estimator's transient response at the rub points with the clearance circle (0,2).

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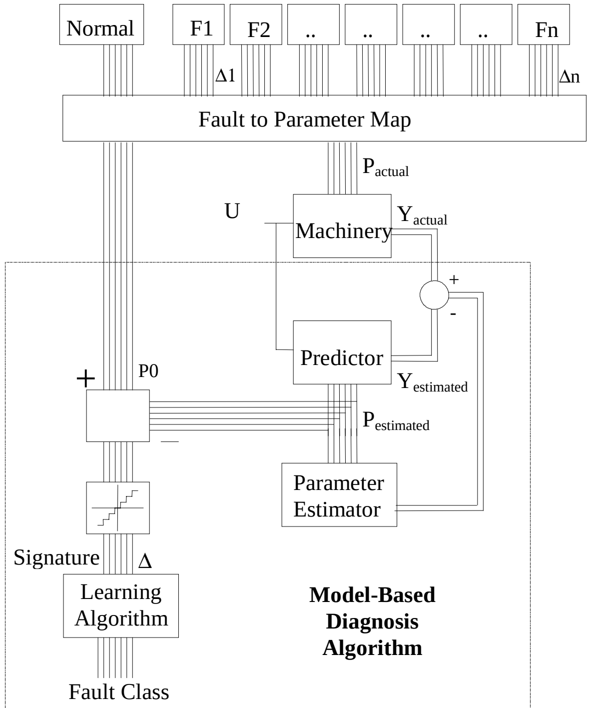

Figure 3. Block diagram of the proposed model-based diagnosis algorithm

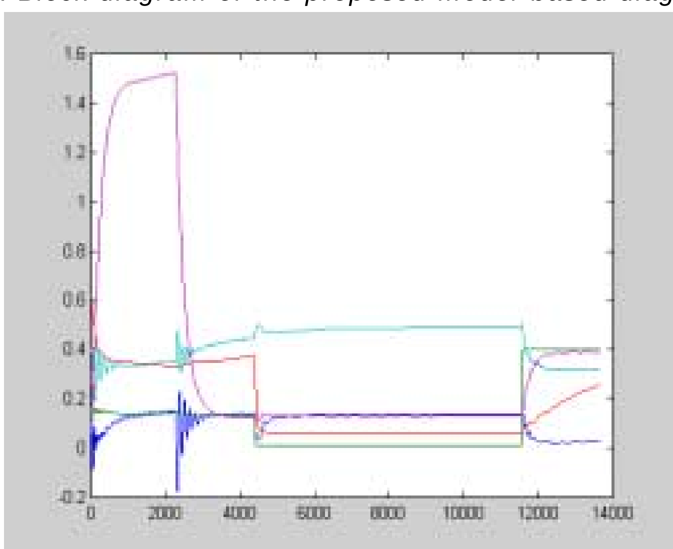

Figure 4. Parameter estimates for a sequence of different fault modes. The fault mode changes every 100 sec (at 0.05 sample/sec).

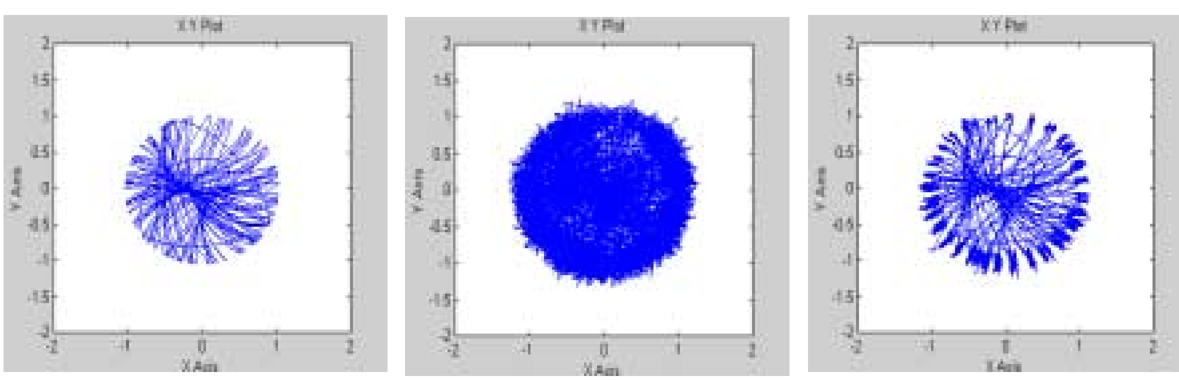

Figure 5. Orbit diagram for fault mode [200,400] sec, of Figure 4. The predicted orbit of the rotor position (Right) is obtained from the simulated data (Middle) based on the estimated parameter. The Predicted orbit correlates to actual orbit (Left) except during transient time.