An Adaptive Remaining Useful Life Prediction Method for Hybrid Ceramic Bearing

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\textbf{Abstract.} Ceramic bearings are quickly replacing conventional steel ball bearings in various fields and applications because they exhibit a service life three times longer than that of steel bearings. However, few studies have been reported on prognostics of ceramic bearings. Compared with the degradation process of steel bearing, the deterioration of ceramic bear contains more nonlinearity and uncertainty. The prediction of Remaining Useful Life (RUL) of ceramic bearings remains a new topic. One of the most challenging problems in the prognostic task is the lack of accurate prediction model. Particularly, when the prognostic model is trained from a data set that undergoes different degradation rate compared with the testing data set due to different load condition and service life for each individual component, the prediction often display large discrepancy. In this paper, a particle filtering based method for hybrid ceramic bearing RUL prediction is presented. An integrated adaptive model based on Recursive Least Square (RLS) is proposed to account the parameter variation of the prognostic model. The method is validated using real hybrid ceramic bearing run to failure test data. The validation results prove the effectiveness and high accuracy of the presented methodology.

\textbf{Introduction}

Ceramic bearings have been widely used critical occasions such as aerospace and precision machinery because their high strength, corrosion resistance and low coefficient of thermal expansion. Ceramic bearings generally present a service life three times longer than that of steel bearings. There are two types of ceramic bearings: hybrid ceramic bearings and full ceramic bearings. Hybrid ceramic bearings are constructed with steel races and ceramic balls while all components are made of ceramic in full ceramic bearings. Various types of ceramic materials were used in bearing applications [1]. Hybrid bearings perform well under extreme operating conditions and offer high-speed operation with low friction. The lower weight of ceramic balls enables rapid accelerations and decelerations. Thermal expansion of hybrid ceramic bearings is about 30% lesser than that of steel bearings [2].

Very few studies have been conducted on prognostics of hybrid ceramic ball bearings using vibration characteristics. Most research has focused studying the characteristics and performance in different applications of ceramic bearings [3-5]. A few papers related to
hybrid ceramic bearing diagnostics and prognostics are worth mentioning here. Dempsey et al. [6-7] summarized the common failure modes of the hybrid bearing and investigated different diagnostic tools, such as magnetic and non-magnetic oil sensors, vibration sensors, etc. Byington et al. [8] developed bearing test system for industrial application, which integrated both time domain and frequency domain analysis. The system is mainly developed for diagnostic purpose for ceramic bearings other than prognostics.

He et al. [9] proposed a Particle Filter (PF) based method for prognostics of hybrid ceramic ball bearings using vibration characteristics. However, PF method was only used for one-step prognostics of the bearing state, i.e., they aim to predict the bearing state within the next sampling interval. Then, an approximated RUL value is calculated based on the predicted machine state. Overall, this paper provided a basic procedure to do one-step prognosis. Later, Ma and He [10] presented an integrated prognostic methodology for direct RUL prediction. They reported higher accuracy and reliability of the RUL prediction compared with [9]. However, a fixed model is used in [10] for the RUL prediction, which cannot account the discrepancy between different testing set and cannot make adaptive correctness over the prediction process, which is main task of this paper. This paper is an extended work based on [10].

Methodology

A practical method for RUL prediction on hybrid ceramic remains largely blank in real situation. The applications of hybrid ceramic bearings may be limited due to the lack of prognostics technology, especially in the fields of aeronautics and space. In order to predict the RUL, a reliable \( l \)-step ahead long term state prediction methodology must be developed. In this paper,

an adaptive RUL prediction method based on the theory of PF and Recursive Least Square (RLS) algorithm was developed. The proposed methodology will be introduced in the following.

Particle Filtering

Particle filters are sequential Monte Carlo methods for state tracking and prediction. The method has been proved effective to model systems including elements of nonlinearity and non-Gaussianity. Particle filtering utilized the information available from both the system measurements and the models available for describing system behaviors [11]. Recently, many successful applications were reported with particle filtering. Saha and Goebel [12] utilized PF to predict the remaining useful life of the Li-ion battery. Cadini et al. [13] use PF based algorithm for modeling fatigue crack growth. In [14], an adaptive algorithm is applied to determine the parameter for the state model of the bearing fault growth model. In this paper, an online adaptive recursive algorithm is utilized to identify the parameter of the state model used in particle filter.

According to the way the data is used to describe the behavior of the system, the fault diagnostics and prognostics can be classified into two categories, data-driven techniques [15] and model-based approaches [16]. Particle filter based method combine these two techniques based on nonlinear dynamic state model, Eq. 1 and Eq. 2. The filtering problem can be formulated as:

\[ x_t = f_t(x_{t-1}, v_{t-1}) \]
\[ y_t = h_t(x_t, u_t) \]  

where \( f_t \) and \( h_t \) are the system state evolution function and observation model respectively. \( x_t \) denotes the states of the system at time \( t \), \( y_t \) the observation, \( v_t \) the process noise, and \( u_t \) the observation noise. More detailed procedure of PF is given in [11].

The most crucial part of PF method is the determination of Eq. 1 and Eq. 2. Physical model and statistical model serve as two different ways to determine Eq. 1. In this paper, we take the first approach but would update the model by Recursive Least Square (RLS) method according to the real time observation data. The physical model Chosen in this paper is Paris’ Law model, which is the most popular model for fatigue crack growth. Eq. 2 could generally be determined experimentally.

**The Paris’ Law model**

The general Paris’s Law model for fatigue crack growth can be given in the following equation:

\[
\frac{da}{dN} = C_0 (\Delta K)^n
\]  

where, \( a \) is the crack length, \( C_0 \) and \( n \) are two material dependent constants and are related to factors such as material properties, environment, etc. \( \Delta K \) represents the range of stress intensity factor over one loading cycle. It is related to the operating load and current damage status. Generally, \( \Delta K \) can be written as:

\[
\Delta K = \rho \cdot a^n \]  

where, \( \rho \) and \( \gamma \) are two parameters related to the stress and current crack size.

Then Paris’ Law model could then be written in a more compact form:

\[
\frac{da}{dN} = C_0 (\rho \cdot a^n)^n = (C_0 \cdot \rho) \cdot a^{yn} = C'_0 \cdot a^{yn'}
\]

where, \( C'_0 = C_0 \cdot \rho \), \( n' = yn \),

Here, \( C'_0 \) and \( n' \) are two adaptive parameters that depends on both material properties and damage status.

A similar Paris’s Law model for bearing defect area growth could be written as follows:

\[
\frac{dD}{dt} = C'_0 D^{n'}
\]

where, \( D \) is the spalled area.

If we take a small enough time interval \( \Delta t \), we can rewrite Eq. 6 in the following format,

\[
D_{t+1} = D_t + \Delta t \cdot C'_0 (D_t)^{n'}
\]

Eq. 7 is the state transfer function, i.e., the state function \( f_t \) in Eq. 1.
Recursive Least Square (RLS)

In the general prognosis process, Paris’ Law model is a deterministic model. It generally works well when used to predict short term state value for a specific rolling machine under certain operating condition. In this paper, since we aim to develop a general model for ceramic bearing prognosis under different operating condition, an adaptive parameter in Paris’ Law would be required to tackle the randomness of the deterioration profile. Also, for RUL prediction, we have to do l-step long term prediction which is more sensitive to parameter setting. In different stages of the bearing’s life time, the inherent Paris’ Law model may display different trends. In order to track the deterioration rate in real time, again it is needed to adaptively change the Paris’s Law parameter according to the latest available information collected from the system.

In order to determine the parameter adaptively on-line, we can take the time domain integration, Eq. 7 can be written as the follow [17]:

\[
\ln(D) = \alpha + \beta \ln(t + t_0)
\]  

(8)

where \( t_0 = [C_0/(1-n')]D_0^{n'+1} \) is the time when the smallest defect area \( D_0 \) occurs, \( \alpha = [1/(n'-1)]\ln[C_0/(1-n')] \), \( \beta = [1/(1-n')] \), and \( t \) is bearing running time relative to \( t_0 \).

By doing the time domain integration, the parameter \( C_0 \) and \( n' \) could be mapped to \( \alpha \) and \( \beta \), which can be represented in a linear function. Since Eq.7 and Eq.8 are mathematically equivalent. We will use Eq.8 in the sequel. There are three parameters in Eq. 8 that need to be identified. These parameters can be estimated by a recursive least square (RLS) algorithm [17]. In order to eliminate the effects of the historic data, a forgetting factor is introduced to the RLS algorithm. The RLS algorithm with forgetting factor is given as follows:

\[
\hat{\theta}(t) = \hat{\theta}(t - 1) + P(t)\psi(t)e(t)
\]  

(9)

where:

\[
e(t) = Y(t) - \hat{Y}[t, \hat{\theta}(t - 1)]
\]  

(10)

\[
\psi(t) = \frac{d\hat{Y}(t, \theta)}{d\theta} \bigg|_{\theta = \hat{\theta}(t-1)}
\]  

(11)

\[
P(t) = \lambda^{-1} \left[ P(t-1) - \frac{P(t-1)\psi^T(t)P(t-1)}{\lambda + \psi^T(t)P(t-1)\psi(t)} \right]
\]  

(12)

In above equations, \( \hat{\theta}(t) \) is the parameter vector, \( e(t) \) is the prediction error, \( Y(t) = \ln(D) \), \( \hat{Y}(t) \) is the estimated value of \( Y(t) \) and \( P(t) \) is covariance matrix. \( \lambda \) is the forgetting factor, typical value is in \([0.95, 1)\).
The Proposed Adaptive Particle Filtering Method

Fig. 1. Adaptive RUL prediction methodology.

Fig. 1 shows the diagram of the proposed adaptive RUL prediction algorithm. First, the initial value of the model parameters needs to be estimated from historical data. Then let us define current time step as $k$, its true failure time step is $k+l$, at which the true state value hit the dangerous threshold. In our real time prognosis solver, we will do RUL prediction by PF at each time step until its failure. That means we will predict RUL iteratively at time step $k$, $k+1$, $k+2$, ..., $k+l-1$, and for each iteration we have to propagate the state value until it reaches the dangerous level. During the process, the PF model will be updated at each iteration using the latest available observation data, which act as the reference for real deterioration situation.

Experiment Verification

An accelerated bearing run to failure test was conducted in a customized bearing prognostics test rig as shown in Fig. 2. The key features of the test rig include:

- It is driven by a 3-HP AC motor with a maximum speed up to 3600 rpm and variable speed controller;
- It is equipped with a hydraulic dynamic loading system with a maximum radial load up to 4400 lbs or 19.64 kN,
- An integrated loading and bearing housing that can be used for testing both ball and tapered roller bearings,
- A support shaft with 2” main diameter balanced with 2 pillow blocks.

Figure 2. Bearing prognostic test rig.
The hybrid ceramic bearings are tested in our test rig under different operating condition. We name the bearings as RTF 13 and RTF 14, respectively. RTF 13 will be used as our ground reference. Both of them were ball bearings with stainless steel inner and outer races and ceramic balls. The observation data was collected every 5 minutes during the test. Therefore, in the following illustration, time step represents 5 minutes sampling interval. At the end of the test, the test bearing was disassembled, checked, and photographed. In the accelerated failure test, 173 data points with the time span of 14.42 hours were used to analysis For RTF 13. For RTF 14, there were totally 804 data points with the time span of 67 hours.

The vibration signals were first pre-processed and the RMS value was chosen to be the fault feature observation data to present the degrading path with respect to the damage developing inside the bearing. The degradation process indicated by the vibration RMS value is shown in Fig. 3.

It can be seen from Fig. 3, the test bearing has a different deterioration process compared with the training data. In order to achieve relative accurate prediction, an adaptive scheme needs to be proposed.

![Figure 3. Training and testing bearing degradation profile as shown by vibration RMS.](image)

Since one cannot directly measure the bearing spoil area, the true hidden state of the bearing can be estimated and represented using the normalized oil debris weight which is assumed to be linearly proportional to the spoil area. Therefore, the state function represented by oil debris weight would also satisfy Paris’ law. The state function is a non-decreasing function of the debris weight which can be obtain by curve fitting the debris weight. The collected oil debris data is shown in Fig. 4. While the observation function builds a relationship between vibration RMS evidence and accumulated debris weight. The failure time is determined by setting a threshold on the debris weight. The ground truth RUL is always a decreasing straight line indicating the time remained for the bearing until it totally failed.
The Results

Since we have 2 groups of data, where RTF 13 data is taken as the ground value, from which we have derived the observation function and the initial Paris Law model parameters. Then we test our methodology with group 14. In our case, 200 particles were used in our estimation. In Fig. 5, we showed several example of the state prediction in \( l \)-step RUL prediction. The red dash horizontal line is the dangerous threshold, which is determined by the result of RTF 13 run to failure data. If the state value crossed this line, we considered the bearing has already broken, i.e., the remaining useful life comes down to zero. Since the true bearing life in the prediction group is 804, 200-step ahead state prediction represents the predicted result at time step 604, without any prior knowledge of the state data or future observation data, and the same analogy for \( l=200,100, 50, \) and 10.

As we can see in Fig.5 above, as \( l' \) decreases, the state prediction error decreases, which means our algorithm converges as the RUL ends. After the state value of the crack area is estimated, the RUL value could be determined by the time when all of the particles crossed the predefined dangerous threshold. RUL mean value is given by the median of the RUL of all particles. Also, a 90% confidential interval is given when 90% of particles have crossed the dangerous threshold. Our algorithm could predict with relatively high accuracy when the \( l \) is within 100 time steps. Fig. 6 and Fig. 7 show the RUL prediction starting at \( l=100 \) and \( l=50 \), separately.
As we can see from Figure 6 and Fig. 7, for RUL prediction of hybrid ceramic bearings, the particle filtering based prognostics algorithm provided very good results. In particular, towards the end of the bearing life, the particle filtering based method converges.

Summary
Particle Filter has been shown to be a very good model for prognosis. However, the quality of the result depends largely on the accuracy of the model. With fixed state transition function, particle filter is only useful for diagnosis of machinery under certain deterioration rate. As for hybrid ceramic bearings, failure time is a random process to a large extent. In this paper, we proposed a particle filter prognosis method with recursive least square optimization scheme. Run-to-failure tests on two hybrid ceramic bearings in a bearing test rig were conducted and vibration data were collected. The collected data was used to test the presented prognostic algorithm. The test results have shown that the presented prognostics methodology is highly effective for predicting the remaining useful life of the testing bearings.

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