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Similarity based method for manufacturing process performance prediction and diagnosis

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Abstract

Full realization of all the potentials of predictive maintenance highly depends on the accuracy of long-term predictions of the remaining useful life of manufacturing equipments. In this paper, we propose a new method that is capable of achieving high long-term prediction accuracy by comparing signatures from any two degradation processes using measures of similarity that form a match matrix (MM). Through this concept, we can effectively include large amounts of historical information into the prediction of the current degradation process. Similarities with historical records are used to generate possible future distributions of features indicative of process performance, which are then used to predict the probabilities of failure over time by evaluating overlaps between predicted feature distributions and feature distributions related to unacceptable equipment behavior. The analysis of experimental results shows that the proposed method can yield a noticeable improvement of long-term prediction accuracy in terms of mean prediction errors over the Elman Recurrent Neural Network (ERNN) based prediction, which was shown in the past literature to predict well behavior of highly non-linear and non-stationary time series.

Keywords: Match matrix; Predictive maintenance; Time series prediction; Failure prediction

1. Introduction

Reducing downtime cost and achieving near zero downtime is the ultimate goal of predictive maintenance. However, it is impossible to realize all the advantages of predictive maintenance without accurate predictions of the remaining useful life before the actual failure occurs. The inaccurate predictive information may result in either unnecessary maintenance, such as early replacement of components, or production downtime because of unexpected machine failures. Therefore, the accuracy of remaining useful life prediction, particularly the long-term prediction, which gives sufficient time to prepare for a maintenance operation, plays an essential role in the full realization of the potentials of predictive maintenance.

The degradation process cannot be directly observed or measured in general. It can only be observed indirectly through the time series of features extracted from available process measurements, such as vibrations and forces. Extrapolating these time series in time can help us to predict risks of failure or unacceptable behavior of the process over time. This places great significance on one's ability to accurately and reliably predict the feature time series. A variety of techniques have been used in the past for time series modeling and prediction. Parametric linear prediction techniques, such as Auto-Regressive Moving Average (ARMA) [1,2] or Kalman filtering [3], may work well only for short-term predictions because of their assumption that the considered time series is generated from a linear process. These linear prediction techniques are well interpretable but with limited capabilities for predicting real world problems which are usually complex and non-linear. Variety of approaches for predicting non-linear time series, such as fuzzy time series and clustering [4,5], multi-resolution wavelet models [6–8] and neural networks [9], has been extensively studied in the literature. Without a priori knowledge

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about the time series under consideration, selecting an appropriate non-linear model and its structure is a difficult task. Among these non-linear prediction technique, neural networks, such as Radial Basis Function (RBF) networks [10] Multi-Layer Perceptron (MLP) neural network [11] and Recurrent Neural Networks (RNN) [12–14], maybe the most extensively applied techniques for complex non-linear time series predictions because of their capability to approximate non-linear functional and dynamic dependencies [9]. Unlike feed-forward networks such as RBF and MLP, which have limitations of identifying temporal relationships in the time series, RNN takes into account temporal dependencies through local or global feedback connections in the network. As a result, RNN is able to approximate a wide class of non-linear dynamical systems [11]. However, the commonly used gradient descent algorithms for RNN training exhibit certain problems during training, such as having difficulty dealing with long-term dependencies in the time series [12], which in turn limits their capability of achieving accurate long-term predictions. In addition, finding a suitable number of hidden neurons and appropriate RNN structure remains a challenging problem.

In many manufacturing facilities, large amounts of historical records of past equipment behavior are available and can be used to enhance and reinforce the equipment performance prediction. The goal of the method pursued in this paper is to increase long-term prediction of signatures depicting equipment performance through incorporation of historical records into the prediction process, while at same time capturing the dynamic changes of the signatures as the process changes.

The following terminology will be used throughout the paper:

- The term *feature vectors* will be used for signatures describing the current state of the machine/process and containing a number of features which are considered to be correlated to the process degradation. The evolution/dynamics of those feature vectors over time is then essentially the characteristic of the degradation process. Once appropriate sensors and adequate features are selected, one can estimate the current degradation state and conduct prediction based on the evolution of the feature vectors.
- The time interval between two consecutive maintenance cycles will be referred to as *a run*. The maintenance operation may be a component replacement, part repair, etc. From the set of sensor readings in each past run, a time-ordered sequence of feature vectors can be extracted to represent the degradation states of the process. The time ordering of the features is necessary in order to be able to explore the temporal evolution of the feature vectors and characterize the process degradation over time.

The rest of the paper is organized as follows. In Section 2, the new match matrix (MM) based prediction method is introduced. The newly proposed approach has been tested on predicting tool degradation in a boring process and the results are shown in Section 3. Section 4 provides conclusions.

2. Match matrix based prediction method

2.1. Concept of a match matrix

We assume that the degradation process is described by a time series of signatures extracted from relevant sensors. The complexity of the degradation process such as tool wear and component aging, often makes the resulting time series so irregular that it cannot be modeled accurately using linear parametric techniques. In order to improve the accuracy the long-term prediction of the irregular behavior of such time series produced by non-linear dynamic systems, a method is needed to effectively utilize the existing historical information about process/equipment behavior over a long period of time. This will involve the comparison of time series from a potentially large number of runs and synthesis of that information into the prediction of the current degradation process.

The Mahalanobis distance is commonly used to evaluate the distance between multidimensional feature vectors whose components are quantities that have different ranges and amounts of variations. The Mahalanobis distance between two n-dimensional feature vectors $\vec{f}^i = [f_1^i, f_2^i, \ldots, f_n^i]^{\mathrm{T}}$ and $\vec{f}^j = [f_1^j, f_2^j, \ldots, f_n^j]^{\mathrm{T}}$ can be calculated as follows [15]

$$d_{i,j} = (\vec{f}^i - \vec{f}^j)^{\mathrm{T}} \Sigma^{-1} (\vec{f}^i - \vec{f}^j) \tag{1}$$

where Σ^{-1} is the inverse of the covariance matrix which can be estimated from samples of feature vectors. The similarity between feature vectors $\vec{f}^i$ and $\vec{f}^j$ can then be expressed as

$$s_{i,j} = \exp(-d_{i,j}) \tag{2}$$

One can note that, if the Mahalanobis distance between two feature vectors is small, then $s_{i,j}$ is approximately 1, while as the Mahalanobis distance between the feature vectors grows, the similarity $s_{i,j}$ between them approaches 0.

If historical records of past signatures collected from several identical machines operating under identical conditions are available to describe various degradation mechanisms, the comparison of two different realizations of the degradation processes involves assessing the similarity between any pair of feature vectors from those two runs. Then, any time a new feature vector $\vec{f}^j_{\mathrm{current}}$ from the current run is extracted, it can be compared with all the feature vectors in the past run by computing the similarities defined by (2). Based on this intuitive concept of feature comparison between the past and the current runs, one can introduce the notion of a *match matrix* as follows.

2.1.1. Definition of a match matrix

Let us assume that there are P feature vectors in the feature vector sequence $\{\vec{f}^1_{\mathrm{current}}, \vec{f}^2_{\mathrm{current}}, \ldots, \vec{f}^P_{\mathrm{current}}\}$ describing the current run, and Q vectors in the feature vector sequence $\{\vec{f}^1_{\mathrm{past}}, \vec{f}^2_{\mathrm{past}}, \ldots, \vec{f}^Q_{\mathrm{past}}\}$ describing the past run. One can compare the degradation patterns of the past and the the current run is being compared through a $Q \times P$ matrix S in