Machine and Process System Diagnostics using One-Step Prediction Maps

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ABSTRACT

This paper describes a method for machine or process system diagnostics that uses one-step prediction maps. The method uses nonlinear time series analysis techniques to form a one-step prediction map that estimates the next time series data point when given a sequence of previously measured time series data points. The difference between the predicted and measured time series values is a measure of the map error. The average value of this error should remain within some bound as long as both the dynamic system and its operating condition remain unchanged. However, changes in the dynamic system or operating condition will cause an increase in average map error. Thus, for a constant operating condition, monitoring the average map error over time should indicate when a change has occurred in the dynamic system. Furthermore, the map error itself forms a time series that can be analyzed to detect changes in system dynamics.

The paper provides technical background in the nonlinear analysis techniques used in the diagnostic method, describes the creation of one-step prediction maps and their application to machine or process system diagnostics, and then presents results obtained from applying the diagnostic method to simulated and measured data.

INTRODUCTION

This paper describes a preliminary investigation of a method for machine or process system diagnostics that uses one-step prediction maps. The main advantages of this method over current predictive maintenance methods are that this method uses time domain data, does not rely on extracting multiple descriptors from the data, and little user expertise is required to interpret the analysis results. We believe these advantages make this method an attractive alternative to current predictive maintenance methods.

Existing diagnostic methods are effective in identifying precursors of equipment failure well in advance of catastrophic failure. However, these methods require specialized equipment and highly trained specialists to properly collect and analyze data and to interpret the analysis results. The relatively high overhead costs associated with this type of predictive maintenance, combined with the lack of an accepted method to estimate the resulting cost savings and the management perception that such maintenance programs are not “essential”, has resulted in many predictive maintenance programs being severely cut back or eliminated.

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A simpler, less costly, predictive maintenance approach may be an attractive alternative for many organizations. The new diagnostic method has the potential for relatively inexpensive implementation requiring a minimum of sensors, specialized equipment, and user expertise. For this reason, we believe the new method may be especially appealing to manufacturing and process industries that recognize the need and benefits of predictive maintenance programs but are unable to commit the resources required to implement current predictive maintenance practices.

A summary of the nonlinear time series analysis techniques used in the creation of one-step prediction maps is presented in the next section along with a description of how one-step prediction maps are formed. This section is followed by a description of how one-step prediction maps are used as a diagnostic tool, forming the basis for the new diagnostic method. The fourth section presents describes applying one-step prediction maps as diagnostic tools to simulated and measured time series. The final section presents conclusions based on the application results.

TECHNICAL BACKGROUND

The diagnostic method uses nonlinear time series analysis techniques to form a map that, given a sequence of time series data points, predicts the next time series point. The map effectively captures the dynamics of the time series, which depend on the dynamics of the system that is generating the time series. Comparison of the predicted values and the subsequently measured values indicates how well the map captures these dynamics. The average difference between the predicted and measured time series values is a measure of the map's error. This error remains within some bound as long as the dynamic system remains unchanged. However, changes in the dynamic system generating the time series results in significant increase in the map error. Thus, monitoring the map error over time should indicate when a change has occurred in the dynamic system.

Neither advance knowledge of the system dynamics to detect the system change nor complicated analysis to interpret the results is required. The level of error simply indicates that some system change has occurred between when the one-step prediction map was created and the current measurement. An extension of the technique would involve calculating maps for multiple machine fault conditions and comparing their prediction errors; the condition corresponding to the smallest map error would be identified as being closest to the current machine condition. A brief description of the nonlinear analysis techniques used to create the maps, the map creation itself, and some relevant results from previous work are given in the remainder of this section.

APPLICATION OF NONLINEAR TIME SERIES ANALYSIS TECHNIQUES

Nonlinear time series analysis techniques are used to determine the optimum time delay used to reconstruct the attractor, and to determine the minimum embedding dimension for reconstruction. If the measured time series is entirely random, any attempt to create a map to approximate and predict the measured time series will be futile. For deterministic systems, the underlying dynamics can be characterized from a time series by applying the method of delays. The dynamics will usually be multidimensional, with the dimension being initially unknown. Once the multidimensional attractor is reconstructed from the measured time series, a map that approximates this attractor can be created.

Attractor Reconstruction

Multidimensional attractor reconstruction is performed by using the method of delays. In this method, vector components are created from a scalar time series by using time series values separated by a delay
time. The number of dimensions used in the attractor reconstruction, \( d_a \), is calculated by using global false nearest neighbors and the optimum time delay, \( \tau \), equals the time corresponding to the first minimum in the mutual information function. Thus, the \( i \)th point of the reconstructed attractor, \( A_i \), is given by

\[
A_i = [t(i), t(i-n_{opt}), t(i-2n_{opt}), \ldots, t(i-d_{opt})]
\]

where \( t(i) \) is the \( i \)th time series point and \( n_{opt} \) is the number of samples corresponding to \( \tau \).

**Mutual Information**

It is generally accepted that the optimum time delay, \( \tau \), used to reconstruct an attractor from a time series corresponds to the time at which the first minimum occurs in the mutual information function. The time delay corresponding to the first minimum in the mutual information function is the minimum time interval necessary for two variables to become essentially uncorrelated. An attractor reconstructed by using \( \tau \) as the delay time will have uncorrelated components while avoiding the "folding" typical of using values of time delay that are too large.

The mutual information function is similar to the autocorrelation function except that it measures the general dependence of two variables rather than only the variable's linear dependence. Note that random data will be uncorrelated, thus, the mutual information function can be used to indicate if a time series contains correlated information from a deterministic source or if the time series is simply random noise.

The derivation of the mutual information function for two series of measurements \( S \) and \( Q \), \( I(S,Q) \), is given in [7]. The resulting expression for \( I(S,Q) \) is

\[
I(S,Q) = H(S) + H(Q) - H(S,Q),
\]

where \( H \) is the entropy of the series of measurements.

If the series of \( N \) measurements \( S \) is given by \( (s_1, s_2, s_3, \ldots, s_N) \), then the entropy, \( H(S) \), is given by

\[
H(S) = - \sum_{i=1}^{N} P_s(s_i) \log_2[P_s(s_i)],
\]

where \( P_s(s_i) \) is the probability of a measurement being equal to \( s_i \).

In a similar manner, if \( S = (s_1, s_2, s_3, \ldots, s_N) \) and \( Q = (q_1, q_2, q_3, \ldots, q_N) \) are two sets of measurements, then the entropy of the combined set of measurements, \( H(S, Q) \), is given by

\[
H(S, Q) = - \sum_{i=1}^{N} \sum_{j=1}^{N} P_{sq}(s_i, q_j) \log_2[P_{sq}(s_i, q_j)],
\]
where \( P_{s,q}(s,q) \) is the probability of \( q \) occurring if \( s \) is known to occur. In this application, \( S \) corresponds to the time series and \( Q \) is obtained from \( S \) by delaying \( S \) by \( \Delta T \).

The mutual information is calculated by using Eqs. (2), (3) and (4) for a range of delay times. For a deterministic time series, plotting the values of \( I(S,Q(\Delta T)) \) (where the dependence of \( Q \) on the delay time is explicitly shown) against delay time results in an initially decreasing values of \( I(S,Q(\Delta T)) \) as delay time increases. \( I(S,Q(\Delta T)) \) eventually will pass through a minimum and will then vary, always remaining at a relatively low value. The value of delay time at which the first minimum of \( I(S,Q(\Delta T)) \) occurs is the reconstruction delay time, \( \tau \), selected to perform the attractor reconstruction.

**Method of Global False Nearest Neighbors**

The method of global false nearest neighbors is based on a simple geometric concept: if the number of dimensions \( d \) used to reconstruct an attractor is too small, many points that appear "near" will become widely separated when \( d + 1 \) dimensions are used in the attractor reconstruction.\(^8\) Nearest neighbor points that experience this wide separation when comparing their distances in dimension \( d \) and \( d + 1 \) are false nearest neighbors in dimension \( d \). Conversely, true nearest neighbors will remain near each other in attractor reconstructions of both \( d \) and \( d + 1 \) dimensions. The adequacy of dimension \( d \) for reconstructing an attractor can be evaluated by selecting a number of random points and their nearest neighbors in dimension \( d \) and then calculating the percentage of false nearest neighbors.

Typical results of this calculation for noise free data show the percentage of false nearest neighbors to be relatively high for low dimensional attractor reconstructions, with the percentage of false nearest neighbors decreasing with increasing dimension, eventually reaching and remaining at a value near zero. The lowest dimension at which the percentage of false nearest neighbors is the minimum embedding dimension needed to reconstruct the data, \( d_e \). Noisy data show similar results, except the percentage of false nearest neighbors reaches a minimum at \( d_e \) and then increases with increasing dimension. The minimum percentage of false nearest neighbors will not approach zero for noisy data; the amount of random noise contamination will determine the value of the minimum in the global false nearest neighbors calculation results.

A pair of points are considered false nearest neighbors in dimension \( d \) if

\[
\frac{R_{d+1}^2(n)}{R_d^2(n)} > R_{tol},
\]

where \( R_d(n) \) is the Euclidean distance between the \( n \)th point and its nearest neighbor in \( d \) dimensions, \( R_{d+1}(n) \) is the Euclidean distance between the \( n \)th point and its nearest neighbor in \( d + 1 \) dimensions, and \( R_{tol} \) is the first criteria for declaring nearest neighbor pairs to be false.\(^8\) A second criteria, needed because near neighbors may not be especially "close", is given by

\[
\frac{R_{d+1}^2}{\sigma^2} > A_{tol},
\]

where \( \sigma \) is the standard deviation of the time series and \( A_{tol} \) is the second criteria for declaring nearest
neighbor pairs to be false. A nearest neighbor pair are declared false if either test (Eqs. (5) and (6)) fails. In our work, the values used for the criteria in Eqs. (5) and (6) have been $R_{vol} = 17.1$ and $A_{vol} = 1.8$.

Description of Radial Basis Function Maps

Previous work has shown that good one-step prediction accuracy can be obtained by using radial basis function maps. The general form of maps composed of radial basis functions is given by

$$x_{i+1} = \sum_{n=1}^{N} \lambda_n \Phi_{n,i}(\|x_i - \alpha_n\|) ,$$  \hspace{1cm} (7)

where $x$ is the time series variable, $I$ is the $i$th iterate, $N$ is the number of terms in the map, $\lambda_n$ is the coefficient (or weight) of the $n$th term, $\Phi()$ is the radial basis function, and $\alpha_n$ is the $n$th basis vector or center. Note that the Euclidean norm between the point $x_i$ and the center $\alpha_n$ is the argument supplied to the function $\Phi()$. Following the example described in [10], the form of the radial basis function $\Phi()$ used in this work is given by

$$\phi(r) = (r^2 + C^2)^{-\beta} ,$$ \hspace{1cm} (8)

here $\beta > -1$, $\beta \neq 0$, and $C$ is a constant. Substituting the Euclidean norm into Eq. (8) for $r$ yields the form for the radial basis function proposed for this work:

$$\Phi_{n,i} = \left( \sum_{k=1}^{d_c} (x_{i,k} - \alpha_{n,k}) + C^2 \right)^{-\beta} .$$ \hspace{1cm} (9)

The values of the $\lambda_n$ are determined by fitting the first $N$ data points. This fitting results in the following equation that must be satisfied by the $\lambda_n$:

$$\{x\}_{i+1} = [\Phi]\{\lambda\} , \hspace{1cm} (10)$$

where $\Phi_{n,i} = \phi_{n,i}$. Singular value decomposition has been used to determine the values of the $\lambda_n$ that give the best prediction of the $x_{i+1}$.

EXAMPLES OF MAP PERFORMANCE

Two examples of map performance are given in this section. The first example is from a map created to model the behavior of the Lorenz system. The second example is from a map created from the noise created by air blowing over a microphone.

Example 1 - The Lorenz System

The Lorenz system is a set of three coupled nonlinear differential equations. This relatively simple system has been a 'workhorse' for nonlinear dynamic studies because it exhibits rich nonlinear behavior.
The Lorenz system is given by

\[ \frac{dX}{dt} = \sigma(Y - X), \]
\[ \frac{dY}{dt} = rX - Y - XZ, \]
\[ \frac{dZ}{dt} = -bZ + XY, \]

where \( \sigma, r, \) and \( b \) are constants and \( X, Y, \) and \( Z \) are the time dependent coordinates.

Equations (11), (12), and (13) were integrated by using a fourth-order Runge Kutta numerical integration algorithm. Values of \( \sigma = 10, \) \( r = 28, \) and \( b = 8/3; \) initial conditions of \( X = 0.01, Y = 0.02, \) and \( Z = 0.15; \) and an integration step size of 0.0005 seconds were used in the calculation. Values of \( X, Y, \) and \( Z \) were tabulated for 0.005 second intervals.

The attractor used in the map calculation was obtained from the \( X \) coordinate by using the method of delays. The optimum time delay for the reconstruction was set equal to the first minimum in the mutual information function and corresponded to 30 samples. The embedding dimension was calculated to be 4 based on the minimum value of the global false nearest neighbor calculation. A 90-term radial basis function map was used to model the time series. K-means clustering was used to select the 90 centers from the attractor; it is felt that selecting the centers in this way ensures that the centers are reasonably representative of the entire attractor.

A comparison of the calculated and the map-predicted values of the time series is shown in Fig. 1. Note that the calculated and the predicted values are nearly identical. The ability of the map to predict the time series so accurately is due mainly to the fact that the time series is noise free. Map error becomes larger for noisy real-world time series.

**Example 2 - A Recorded Time Series**

The second example uses a recording made of air from a fan blowing over a microphone as the time series. The recording was digitized at a sample rate of 11025 Hz and stored as 16-bit integers. The frequency response of the microphone is unknown but is not believed to be of particularly high fidelity. The time series is shown in Fig. 2.

The optimum time delay for the reconstruction was again set equal to the first minimum in the mutual information function and corresponded to 38 samples. The embedding dimension was calculated to be 4. A 90-term radial basis function map was used to model the time series.

A comparison of the calculated and the map-predicted values of the time series is shown in Fig. 3. Note that the map accurately predicts the recorded time series but that the agreement between the measured and predicted values is poorer than was obtained with the Lorenz system. The poorer agreement is attributed to the presence of measurement system and random noise in the recorded signal.
Figure 1. Comparison of calculated and map-predicted values for the Lorenz system. The values have been normalized to be between +1 and -1.

Figure 2. The normalized time series obtained from the recording.
Figure 3. Comparison of the measured and predicted time series for the recorded data.

APPLYING ONE-STEP PREDICTION MAPS TO THE PROBLEM OF MACHINE OR PROCESS SYSTEM DIAGNOSTICS

The application of one-step prediction maps for diagnosing machinery or process system condition is straightforward. A baseline time series is collected from the machine or system during normal operation. The nonlinear time series analysis techniques described above are applied and a suitable one-step prediction map is created. This map is then used to calculate the average map error for the baseline time series.

Once the one-step prediction map and the average absolute map error for the baseline time series are obtained, monitoring is performed by using the one-step prediction map to periodically calculate the average absolute map error using a current time series. The current value of map error is compared with the map error calculated for the baseline time series. A significant increase in the map error indicates that a change in the system has occurred.

It seems unlikely that the determination of what constitutes a “significant” map error change can be made without resorting to data collected from the machine or system operating over a range of conditions. Thus, before one-step prediction maps can be used for monitoring, map errors for a range of known conditions should be calculated. These map errors can then be used to determine whether a given map error change is significant or falls within normal variations.

A variation of this approach is to calculate one-step prediction maps for each of the known conditions. A crude diagnosis could be performed by calculating the map error for a given time series using one-step prediction maps corresponding to each known condition. The current condition would be diagnosed as being the one corresponding to the condition used to create the one-step prediction map that gives the smallest map error.
APPLICATION RESULTS

Use of one-step prediction maps as indicators of changes in dynamic systems was investigated by using simulated time series and measured time series. Advantages of using simulated time series in the method evaluation are that dynamic system changes are of known magnitude, occur at known times, and the time series are noise free. The advantage of using a measured time series in the method evaluation is that the method performance can be evaluated under real-world conditions, where noise and uncertainty exist. The use of both simulated and measured time series provides a reasonable evaluation of the method's potential for use in machine or process system diagnostics.

TEST OF THE DIAGNOSTIC METHOD BY USING A SIMULATED TIME SERIES

The first tests of the diagnostic method were performed by using simulated time series. The Lorenz system of equations was selected as the dynamic system. This system experiences chaotic behavior for a proper choice of the parameters \( \sigma, r, \) and \( b \). In this work \( \sigma = 10 \) or 12, \( r = 28 \), and \( b = 8/3 \); these values result in chaotic dynamic behavior.

Effect of Parameter Change on the Average Map Error

Three time series spanning a period equivalent to 400 seconds were created by integrating Eqs. 11, 12, and 13. The calculated data was recorded for time intervals of 0.005 seconds. A \( \sigma \) value of 10 was used during the first 200 seconds and a \( \sigma \) value of 12 was used during the final 200 seconds. The initial 100 seconds of data were discarded to avoid the initial transient.

The time series corresponding to the \( X \) component was used in the test. The calculated first minimum in the average mutual information function was equal to 0.16 seconds and the calculated embedding dimension was 5. A 90-term radial basis function map was created by fitting the first 10000 stored time series points; these points were calculated by using a value of \( \sigma = 10 \). The map error was calculated for each point in the time series and evaluated for an indication of the change in the value of \( \sigma \) at \( t = 100 \) seconds.

Figure 4 shows the map error for entire time series. During the first 100 seconds, the average map error equals -0.0008 and the standard deviation = 0.00186. During the final 200 seconds, the average map error equals -0.00018 and the standard deviation = 0.00338. The average map error clearly indicates that a parameter change, i.e., a change in the system dynamics, occurred at approximately \( t = 100 \) seconds. These results show that for a noise-free time series, the average map error can indicate a change in system dynamics. Furthermore, if a dynamic change occurs at a particular time \( \tau \), the effect of that dynamic change on the map error will occur at the time \( \tau + \Delta \tau \), i.e., one sample after the change occurs.

Effect of Adding a Sine Wave to the Time Series

A second example using simulated data involved adding a sine wave of unit amplitude and a frequency of 1 Hz to the \( X \) component for \( t > 100 \) seconds. The previously-calculated 90-term radial basis function map was used in this example. The map error was calculated for the time series and transformed into the frequency domain.

Figure 5 compares the frequency spectrum for the map error time series containing the added sine wave (\( t > 100 \) seconds) with the frequency spectrum for the map error time series with no sine wave (\( t < 100 \) seconds). Note that the 1 Hz component is clearly visible in the spectrum containing the sine wave and
that the amplitude of this spectrum is considerably greater than that of the spectrum without the sine wave, a finding consistent with the results of the previous example.

Figure 6 compares the frequency spectra of the $X$ component of the Lorenz attractor with the added sine wave with the $X$ component of the Lorenz attractor with no sine wave. The comparison shows no significant differences between the two spectra.

These results indicate that the map error may be a sensitive indicator of changes in the time series dynamics and that its frequency domain may be superior to its time domain for detecting changes in a time series. The spectra of the map errors shown in Fig. 5 show marked differences in both amplitude and frequency content. Also, Fig. 5 shows that if a dynamic change of a particular frequency occurs, that frequency is preserved in the map error. This result is important because many common machinery faults occur at known ratios of the machine operating speed. Thus, the same diagnostic rules used to interpret machinery vibration spectra may be applied to interpret map error spectra.

Comparing Figs. 5 and 6 show that the sine wave is not detectable in the time series spectra, but is easily detected in the map error spectra. This result implies that a dynamic change may be detectable in the map error spectrum before it could be detected in a spectrum formed from the measured time series. More generally, the results of investigating the effects of adding a sine wave to a time series agree with the previously shown results; the map error is seen to be very sensitive to changes in time series dynamics. In addition, the results show that if a dynamic change occurs at a particular frequency, the effect of the dynamic change on the map error will occur at that same frequency.
Figure 5. Comparison of the map error spectra with and without the added sine wave.

Figure 6. Comparison of the spectra of the Lorenz attractor $X$ component with and without the added sine wave.
TEST OF THE DIAGNOSTIC METHOD BY USING A MEASURED TIME SERIES

RF data collected to investigate the feasibility of remotely monitoring motors was used to test the method by using measured data. The data was collected for a range of motor load currents.

The data was collected at a sample rate of 2 MHZ and immediately low-pass filtered using a cut-off frequency of 1 MHZ. Two seconds of data were collected in each file and three files were stored for each motor current value. A summary of the data files is shown in Table 1.

Table 1 - Summary of RF Data Files

<table>
<thead>
<tr>
<th>File Designator</th>
<th>Motor Current (amperes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1, 2, &amp; 3</td>
<td>26</td>
</tr>
<tr>
<td>4, 5, &amp; 6</td>
<td>61</td>
</tr>
<tr>
<td>7, 8, &amp; 9</td>
<td>123</td>
</tr>
<tr>
<td>10, 11, &amp; 12</td>
<td>160</td>
</tr>
<tr>
<td>13, 14, &amp; 15</td>
<td>202</td>
</tr>
<tr>
<td>16, 17, &amp; 18</td>
<td>221</td>
</tr>
<tr>
<td>19, 20, &amp; 21</td>
<td>249</td>
</tr>
</tbody>
</table>

A time series taken from the data file corresponding to the lowest motor current value used in the test was used as the baseline time series. This data was low-pass filtered, down sampled by a factor of 30, and used to form a 30,000-point baseline time series. The down sampling was performed to allow a larger time interval to be used in the map error calculation without making the number of points in the baseline time series unwieldy. A 90-term radial basis function map was created by using a reconstruction time delay of 54 samples and an embedding dimension of 8.

High correlation between the average absolute map error and the motor current is shown in Fig. 7. This result indicates that map error is sensitive to changes in real systems and may be sufficiently robust to be used with measured data.

Figure 7. Average absolute map error for RF data.
SUMMARY

The present work indicates that the map error formed by using one-step prediction maps can be used to indicate when a system has experienced a change affecting its dynamics. The ability to detect changes in the time series of dynamic systems such as machinery or process systems allows the map error to form the basis for a form of machine or process system diagnostics. This form of diagnostics can be reduced to an overall measure of "sameness" characterized by the comparison of the average absolute map errors for baseline and subsequent time series.

It has been shown that the map error for a synthetic system (the Lorenz system) can successfully be used to indicate when a system parameter change occurs. Furthermore, it has been shown that in addition to giving an indication characterizing the overall behavior of a time series (i.e., the average absolute map error for a time series), the map error itself forms a time series with enhanced sensitivity to system changes. It has been shown that if a significant change occurs in a dynamic system at a time \( \tau \), the effect on map error time series will occur at time \( \tau + \Delta \tau \). Necessarily, if a significant change occurs in a dynamic system at a particular frequency, the map error time series will show the change at that same frequency. This result means that known relationships between running speed and particular faults, which are well known, can be used to diagnose the cause of peaks in map error frequency spectra.

The application of map error to detect changes in the operating conditions of a motor has shown that the map error can indicate when a parameter change (in this case the motor current) occurs. This result indicates that the map error may be sufficiently robust to be used with measured data and is not limited to laboratory data or mathematical simulations.

Map error, either as an overall indicator of time series "sameness" or as a time series analyzed independently, shows some promise for performing machine or system diagnostics. The current results indicate that further exploration of the potential of this approach may be warranted. Further exploration should concentrate on evaluating the effectiveness of map error for detecting changes in measured time series obtained from either machinery or process systems.

REFERENCES


