Data Driven Autonomous Fault Detection and Identification Methodologies

- Literature Review on Similarity Based Modeling for Fault Detection and System Monitoring

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Abstract: Compared to methods built upon first-principle models, data-driven health monitoring and fault diagnosis methods have shown superior performance in terms of quick in-time modeling, adaptability and versatility towards plant variations. Combined with online adaptive estimation/prediction and machine learning algorithms, prompt fault diagnosis, prognosis and even Remaining Useful equipment Life (RUL) estimation are made possible. In this report, we will review several key research results that are commercialized and implemented by GE SmartSignal® technology.

- GE SmartSignal® software

As the core of GE's asset performance management system, GE SmartSignal® offers cloud based software solutions across all equipment, plant and fleet to cover critical needs of industries, such as machine health monitoring, reliability management, optimized maintenance planning, etc. One of the highlights is about modeling. This technology is based on data-driven modeling approaches, which are covered by over 40 patents. Instead of using simple thresholding of actual variable values, it adopts empirical modeling by leveraging and aggregating sensor data to achieve early fault detection. For this purpose, the differences between the actual measurements and the predicted normal values (from the constructed normal baseline models) are evaluated. Then diagnosis and prognosis are performed to detect the developing problems and predict the onset of severe failures. The following summarizes the features claimed by GE SmartSignal:

- Scalable and configurable data-driven modeling;
- Early incident alerts
- Predictive-diagnostics
- Cloud based, easy deployment

- Similarity-base Modeling in SmartSignal Technologies, [1][2]

We have reviewed several research papers and patents (with SmartSignal Corp. as the assignee) documenting related techniques.

An empirical data-driven surveillance system is described in the U.S. patents to Gross et al., consecutively in 1998, and 2001, [1][2]. It is one of the earliest similarity based technologies that has been adopted by SmartSignal®. A schematic diagram for this surveillance system is given in Fig. 1. It contains 4 main modules: a *reference library* storing known states of the monitored process; an *empirical model engine*, acting as a similarity based state/parameter estimation scheme, which generates estimates of the current process states; a *pattern recognition* module, for which a sensitive statistical hypothesis test, such as Sequential Probability Ratio Test (SPRT), is implemented to determine whether the current process state belongs to normal or abnormal states; and finally a *diagnostic* module, in which a simple lookup table of fault modes is used in [1][2]. But one can also implement more sophisticated failure/fault classification approaches for diagnostics. In addition, *time correlation* is a necessary pre-processing module, since time lags exist among different sensor measurements from various sensors installed in distributed locations of the process. For this reason cross-correlation between different data vectors is calculated based on which the time shifts are determined, and the data vectors aligned.

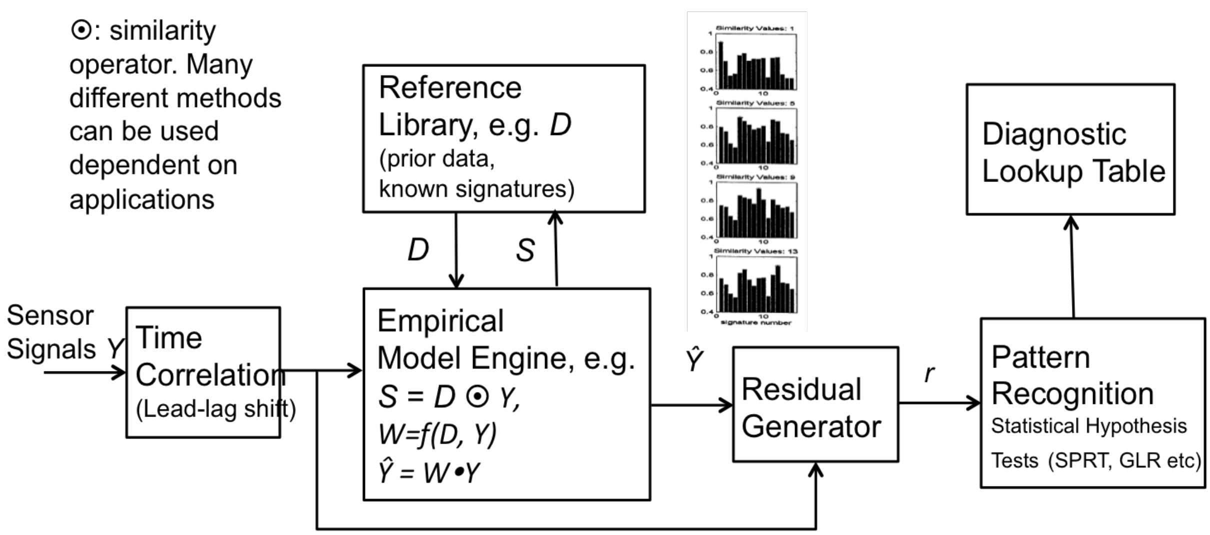

Fig. 1. A similarity and pattern recognition base FD scheme

The role of the similarity operator in the empirical model is to determine a metric of the similarity of a current set of sensor readings to any of the 'snapshots' of sensor readings contained in the reference library (denoted by D, the learned-state matrix). One example of such a similarity operator is distance measures between vectors and arrays, e.g. Euclidean distance. The similarity metric rendered is then used to generate an estimate of the *expected true* sensor measurement: First based on analyzing the association of the current sensor measurement with the learned-state matrix D, the closest state(s) matching the current sensor measurement is determined, and the corresponding weighting parameters are implemented as

W; Then the true sensor measurement is calculated, i.e. $\hat{Y}$. The estimate can then be compared to the current measurement to generate residual signals indicating incipient process upset and sensor failures. Different multivariate state and parameter estimation techniques, such as auto-regression moving average (ARMA) based, Kalman filters, partial lease square (PLS) methods, and even neural network (NN) models can be adopted for the above estimation problem. The more detailed and thorough procedures for this data driven surveillance system are illustrated in the problem flowchart, shown in Fig. 2 (the original Fig.1 in [1][2])

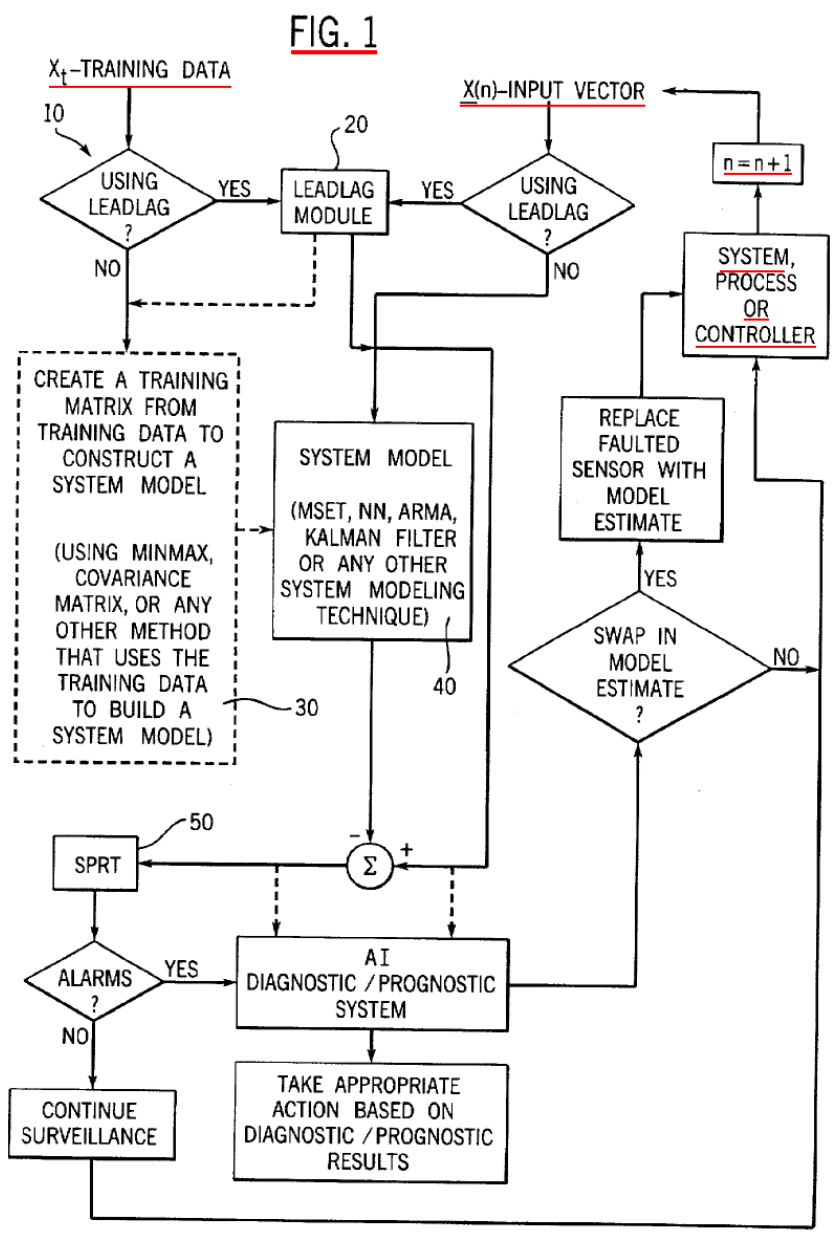

Fig. 2. Flow chart of the data driven surveillance system, [1][2]

- Improvement made for SBM based monitoring system, [3][4][5]

  As mentioned in the above, such a monitoring system utilizes statistical tests such as sequential probability ratio test (SPRT). However successful application of statistical tests to the residuals of the above system is contingent on several assumptions. First it is assumed that if the monitored system is behaving normally, the residual resembles (a function of) Gaussian white noise. However, noises in the real plant or process will not always be i.i.d. (independent and identical) Gaussian. Second, in the above data driven monitoring system, under no-fault conditions, this residual is often a function of the quality of the data used to train the model. The performance of the monitoring system depends heavily on the availability of 'high-quality' training data, covering various operation ranges of the monitored system and process. The above assumptions simply impose strong constraint on training data, which can rarely be satisfied in practice. Implementation of the similarity based empirical model, coupled to a SPRT alert generation module can result in a high rate of nuisance alerts, especially if the model is established using limited training data for the expected range of operations of the process or machine being monitored, [2].

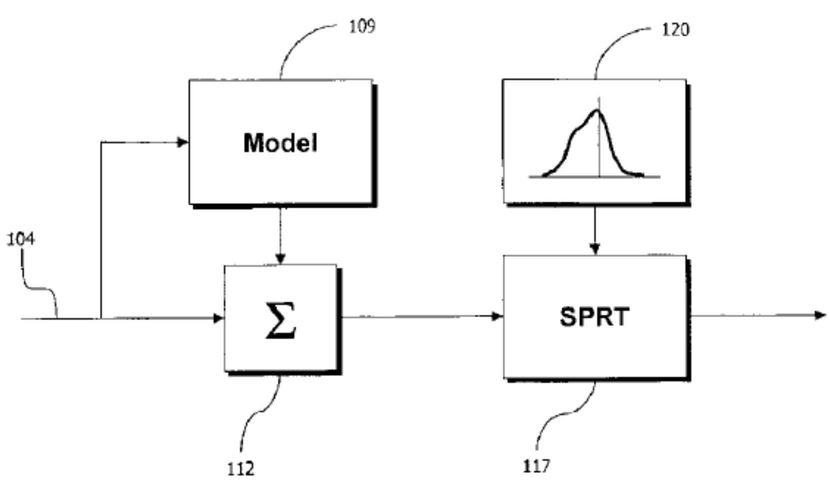

Fig. 3. SPRT based fault detection, [3]

Similarity based modeling (SBM) was further improved in a latter US patent to Wegerich etal. Particularly improvement was focused on the SPRT module. To overcome the strong assumptions, inherent to the SPRT based hypothesis test, an approximated SPRT is proposed in [3]. The modified SPRT utilizes an empirically derived distribution specific for each residual. For this purpose, residual values are organized in a histogram, and then normalized to provide an approximate distribution shape. A curve defining the distribution contour can then be approximated with piece-wise function fitting, such as spline techniques (B-spline and cubic spline etc.), to obtain an empirical distribution. Such an empirical distribution provides the successive likelihood values for successive residual data points in the SPRT test. Therefore the step in SPRT using Gaussian function to calculate the likelihood values can be replaced. Such an improvement renders an algorithm that can be easily programmed for different applications with data of non-Gaussian distributions. What is interesting is that this empirical distribution derivation is actually like a 'learning' step, which makes the improved similarity-based modeling suitable for many different applications. Furthermore, such an approximated empirical distribution is still available even if a limited number of test data are used to generate the histogram. This improved version of the SBM based monitoring system is generally applicable to multivariate condition monitoring problems, by allowing different empirical distribution derivation for different sensor readings.

In [4], the SBM is adopted for vibration machine condition monitoring. In a more recent patent granted to the same researchers [5], the empirical modeling engine, as shown in Fig. 1, is adopted in combination with a complex signal decomposition technique (e.g. Wavelet analysis), to extract multivariate information from one single complex signal. This invention was clearly targeted at the signal based condition monitoring problems, e.g. rotating machine monitoring based on vibration signals. The extracted signal components are provided as inputs to the empirical modeling engine (see Fig. 4). Similarly the empirical modeling engine compares the extracted component inputs against expected values in the reference library to extract more information about the actual signal or about the state of the system generating the signal, [5].

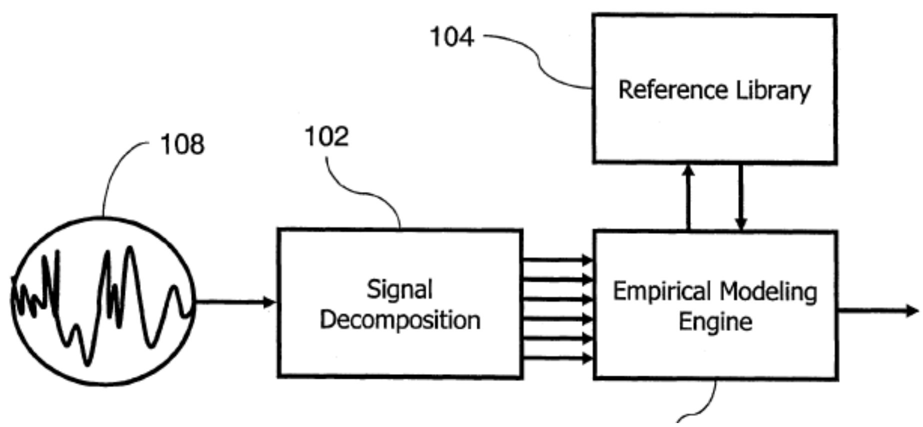

Fig. 4. Similarity-based modeling (SBM) with signal decomposition module for signal based condition monitoring (originally Fig. 1 in [5])

- Kernel regression modeling for predictive condition monitoring system, [6]

Kernel regression is a more general form of modeling used to determine a nonlinear function or nonlinear relationship among different variables in a dataset. It has recently be used to monitor machines or systems to determine their conditions. In fact, the similarity based regression modeling is one type of kernel regression, where the similarity operation is regarded as the kernel function, which compares the current sensor reading to the known state stored in the learned-state matrix *D* (See Fig. 1). In this invention, it is possible to adopt other forms of kernel functions for the regression based modeling, e.g. polynomial, radial basis function (RBF), or Nadaraya-Watson kernel smoother (for reducing noise).

The accuracy of the estimates in a kernel regression model can be greatly improved by incorporating time domain information into the model. In earlier versions of the similarity based empirical modeling scheme, the input data is treated as distinct and disconnected 'time-contemporaneous' patterns when calculating the estimates of the sensor readings. Therefore one objective of the recently developed monitoring system and method in [6] is to generate estimated data by capturing time domain information from the large numbers of periodic and non-periodic sensor signals that are used to monitor industrial processes, systems, machines, or other assets. In addition, in the empirical model adopted in [6], the fundamental nonlinear mathematical relations at the core of kernel regression modeling are extended from a vector-wise operation to a matrix-wise operation. This extension is extremely important, in order to include time-ordered input vectors in the scheme. Due to the inclusion of time-domain information, another improvement of the kernel repression based monitoring system in [6] is to generate virtual or inferred estimate values for future time points to determine a future condition of the object being monitored. This is particularly interesting for trend prediction and fault prognosis.

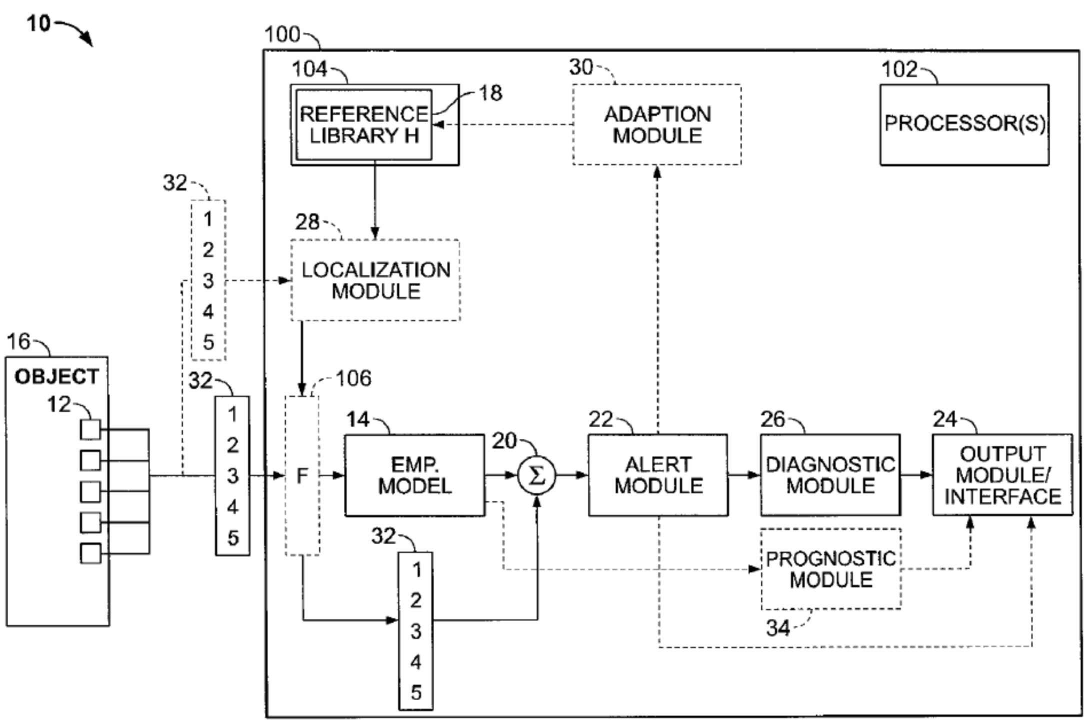

Fig. 5. A monitoring scheme using kernel regression and input pattern sequences, [6]

The monitoring scheme proposed in [6] is given in Fig. 5. It is clear that it follows similar design concept as the SBM based surveillance system proposed in [1]-[3]. What is different is that the input is the sequence of data vectors, i.e. input data array (matrix), instead of distinct data points. For this reason, the learned-state matrix from the reference library is $D(t)$, a 3-dimensional array. This monitoring system also may have a *Localization Module* that changes which data from the reference library is used to form the matrix $D(t)$ to compare to the vectors in each input array. An adaptation module may be included that continuously load the input vectors into the reference library to update the library. It can also be used to update the system state in the library when a new event occurs, for example, when the model receives data that indicates a new normal operation condition of the machine. Among all the similarity based modeling schemes for fault diagnosis and system monitoring, the invention in [6] is no doubt one of the most general and improved methods that has been adopted in the SmartSignal technology.

Concluding Remarks:

This report is focused on reviewing technical concepts (core ideas) and design considerations of the process and machine health monitoring solutions by GE's SmartSignals. Similar types of analysis methods are also offered by Expert Microsystems, which uses a similar auto-associative kernel method for calculating residuals, and it also has other modules for diagnosis and prediction.

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