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A Survey of Data-Driven Prognostics

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Integrated Systems Health Management includes fault detection, fault diagnosis (or fault isolation), and fault prognosis. We define *prognosis* to be detecting the precursors of a failure, and predicting how much time remains before a likely failure. Algorithms that use the *data-driven* approach to prognosis learn models directly from the data, rather than using a hand-built model based on human expertise. This paper surveys past work in the data-driven approach to prognosis. It also includes related work in data-driven fault detection and diagnosis, and in model-based diagnosis and prognosis, particularly as applied to space systems.

I. Introduction

NASA is currently planning long-duration human space exploration missions to the Moon and Mars. Reliability of the spacecraft will be extremely important for these missions, since they will be away from the Earth for months or years at a time. An important contributor to that reliability will be an on-board Integrated Systems Health Management (ISHM) system. ISHM can provide two advantages. First, it can increase safety, by detecting problems and quickly diagnosing them before they become serious, so that controllers can respond rapidly and prevent major failures. Second, it can reduce costs by avoiding unnecessary maintenance and enabling maintenance to be scheduled more efficiently. Maintenance scheduling is most important for reusable systems, such as aircraft or the Space Shuttle, but even expendable piloted spacecraft, such as Apollo or Soyuz, have some maintenance actions that can be performed by the astronauts during a mission.

An ISHM system takes as input sensor values and the command stream, and ideally performs fault detection (detecting that something is wrong), fault diagnosis (determining what is wrong; also known as fault isolation), and fault prognosis. We define prognosis to be detecting the precursors of a failure, and predicting how much time remains before a likely failure. We believe that prognosis is the most difficult of the three tasks. One must be able to detect faults before one can diagnose them. Similarly, we believe that one must be able to diagnose faults before one can perform prognosis. In addition to fault detection, diagnosis, and prognosis, ISHM also includes support for deciding what actions to take in response to a failure or a failure precursor. These actions can include reconfiguration of redundant hardware, maintenance actions performed by the crew, maintenance actions performed on the ground (for reusable vehicles), and mission replanning to accommodate degraded systems. The field of ISHM is often considered to include sensor development and optimization of sensor placement, but this survey focuses only on the algorithms used for fault detection, diagnosis, and (especially) prognosis.

A simple form of prognostics, known as a life usage model, is widely in use. This method is applicable to components that have been mass produced. It gathers statistical information about the amount of time that a component lasts before failure, and uses these statistics collected from a large sample of components to make remaining life predictions for individual components. These predictions are based solely on the passage of time and/or measures of usage of the system or component. For example, for a timing belt on an automobile, the manufacturer may recommend that the belt be replaced after five years or 60,000 miles. These prognostic recommendations are not based on any measured characteristics of the individual component. This survey is primarily concerned with prognostic methods that take advantage of measured characteristics of individual systems or components in order to make predictions, and not on life usage models.

One approach to prognosis is to use a hand-coded, physics-based model of the system. Another approach is the expert system approach, which uses a hand-coded, rule-based model of the system.[1] A third approach is the data-driven approach, also known as the data mining approach or the machine learning approach, which uses historical data to automatically learn a model of system behavior. Hybrids of these three approaches are also possible. This paper surveys past work in data-driven prognosis of complex engineered systems. The survey includes hybrid

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methods that combine the data-driven approach with one or more of the other approaches. In addition to surveying data-driven approaches to prognosis, we also briefly survey data-driven approaches to fault detection and diagnosis, and model-based approaches to diagnosis and prognosis, especially as they have been applied to space systems.

The sections that follow are each devoted to one of the approaches described above. Since many systems use a combination of these approaches, they could fit into more than one of these sections. We have chosen, however, to include each system in the one section in which we feel it best fits.

II. Data-driven prognosis

Many of the existing approaches to data-driven prognosis have used artificial neural networks to model the system.[2,3,4,5] Artificial neural networks are a type of model based loosely on the neural structure of the brain, in which the weights of the connections among neurons are automatically adjusted to maximize the fit of the model to the data.[6]

Much of the work in prognostics has been for structural prognostics. Many such systems use vibration sensors to monitor the health of rotating machinery such as helicopter gearboxes[7] or jet engines.[4] Doebling *et al.* provide an overview of vibration-based damage assessment.[8] Lebold *et al.* provide an overview of various preprocessing algorithms that can be applied to vibration data before it us used for diagnosis or prognosis.[9] Some systems monitor the exhaust gases or the oil stream from an engine for contamination that could indicate a fault.[10]

Wang and Vachtsevanos propose an architecture for prognosis that uses dynamic wavelet neural networks (DWNN), reinforcement learning, and genetic algorithms. Their target application is industrial chillers. They test their proposed architecture using vibration data from an intentionally cracked bearing. They define five prognostic performance measures, and show that the DWNN method outperforms an autoregressive method on these measures for the bearing data. For a second data set, they use vibration data from a mixer – a motor connected to a long rod connected to a fan – in which the fixture connecting the motor to a wall had been intentionally loosened. The DWNN appears to work well for this data set too.[2]

Brotherton *et al.* combined neural nets with rule extractors and applied it to gas turbine engine prognostics. Their system first fits a Dynamically Linked Ellipsoidal Basis Function (DL-EBF) neural network to the vibration data, and then fits a decision tree to the neural net, which can be used to help understand the model. They applied their system to vibration data from seeded-fault test stand operation of a jet engine.[4,11]

Parker *et al.* used polynomial neural networks, and trained them using vibration data from seeded faults in helicopter gearboxes.[5]

Wegerich *et al.* used a similarity-based method for data-driven prognostics.[12] Their method makes predictions using an average of the training data, weighted based on a similarity measure. They assert that their system is applicable to any multivariate data stream in which a consistent relationship between individual streams exists, but the paper focuses on vibration data from rotating machinery. They use data obtained from a laboratory mechanical test system with induced faults. They demonstrate that their methods can help to detect certain induced faults, but leave estimation of useful life remaining as future work.

Prognostics for batteries appears to be at a more advanced stage than prognostics for structures. One could say that the battery gauge software in a typical laptop computer does prognostics, since it estimates the amount of time remaining before the battery runs out of charge. Shimanek presents a system for battery prognostics that estimates state of health and state of life of a rechargeable battery, in addition to state of charge, using a combination of autoregressive moving average, neural net, and fuzzy logic algorithms. After testing showed a high level of accuracy, the prognostic system began testing in simulated military field conditions.[3]

Byington, *et al.* describe an approach that uses a Bayesian Belief Network for diagnosis of aircraft avionics. They have built a prototype system for diagnosing faults in an aircraft autopilot. They also describe their plans to extend the approach to prognostics.[13]

Atlas *et al.* present an architecture that combines the model-based and data-driven approaches to fault detection, diagnosis, and prognostics for aircraft.[14] It includes a prognostic reasoner that takes as input the outputs from a variety of specialized prognostic algorithms for different systems within the aircraft, and then prioritizes the most probable failure modes. The system uses an integrated model to predict how a probable failure will affect systems throughout the aircraft. It also compares the outputs of the anomaly detector, the diagnostic system, and the prognostic system to see whether the three types of algorithms corroborate each other. The paper focuses primarily on the architecture. It includes a brief description of some fault detection and diagnostic algorithms that the authors have used with the architecture, but no description of prognostic algorithms.

The Joint Strike Fighter (JSF) aircraft is currently under development.[15] It will be used by the U.S. Air Force, Navy, and Marines, and by certain U.S. allies. The current plan is for it to have a Prognostics and Health

Management (PHM) system that provides fault detection and isolation for every major system and subsystem on the aircraft, and prognostics for selected components. PHM is intended to both improve safety and reduce maintenance costs. It will use model-based, rule-based, and data-driven approaches. The proposed architecture includes an off-board PHM system (OBPHM), which will use data mining techniques.[10,16,17]

III. Data-driven fault detection

Park, *et al*. applied the BEAM (Beacon-based Exception Analysis for Multi-Missions) system to anomaly detection in Space Shuttle Main Engine data[18]. BEAM has nine components that use nine different approaches to anomaly detection. The work described in Ref. 18 only used one of the nine components: the Dynamical Invariant Anomaly Detector (DIAD). DIAD is an unsupervised anomaly detection algorithm, which looks for anomalies in one variable at a time. Park, *et al*. trained DIAD using data from 16 nominal tests, and tested it using data from seven tests that contained known failures. It detected all of the major failures in these seven tests, although it missed some minor failures and had some false alarms.

Schwabacher used two unsupervised anomaly detection algorithms, Orca and GritBot, to look for anomalies in data from two rocket propulsion systems, the Space Shuttle Main Engine and rocket engine test stand E-1 at NASA Stennis Space Center.[19] These algorithms support both discrete and continuous variables, and look for anomalies in the relationships among the variables, in addition to looking for anomalies in the individual variables. The algorithms detected some anomalies that were already known to the experts, and some others that were not known to the experts but were not considered to be significant.

Iverson's Inductive Monitoring System (IMS)[20] is another unsupervised learning system for fault detection. It uses a clustering algorithm to cluster the nominal training data into clusters representing different modes of the system. When new data fails to fit into any of the clusters, it signals an anomaly, using the distance from the nearest cluster as a measure of the strength of the anomaly. After the STS-107 Space Shuttle Columbia disaster, Iverson applied IMS to some relevant data. He trained it using data from five previous Space Shuttle flights, and then tested it using STS-107 data. It detected an anomaly in data from temperature sensors on the Shuttle's left wing shortly after the foam impact, suggesting in retrospect that with the aid of IMS, flight controllers might have been able to detect the damage to the wing much sooner than they did.

Oza *et al.* used neural nets and ensembles of neural nets for helicopter fault detection.[21] Their method of detecting a fault is to assume that a fault has occurred when an actual maneuver fails to match a predicted maneuver. The data they used included vibration data from the gearbox, angular velocity and torque of the planetary gear, and altitude, velocity, and orientation of the helicopter, from a set of experimental flights in which the pilot always performed a predetermined maneuver. They obtained very high accuracy rates at predicting the maneuver, especially when using ensemble methods. It remains to be seen whether failure of their method to predict a maneuver will be highly correlated with faults, as they have hypothesized.

Srivastava presents algorithms based on envelope detection and dynamic hidden Markov models for detecting anomalies in time series data with large numbers of discrete and continuous variables.[22] He tests the algorithms using synthetic data motivated by a fleet of aircraft.

IV. Data-driven diagnosis

He and Shi found that support vector machines (SVM) produced better accuracy than artificial neural networks when applied to the diagnosis of faults in valves in reciprocating pumps, using vibration data.[23] They used a wavelet packet transform (WPT) to preprocess the vibration data, extracting the time and frequency information, and then used the SVM to classify the faults. Further research is needed to determine whether approaches such as SVMs would produce accurate results for prognosis problems.

Much work has been done with the intention of diagnosing problems in helicopter gearboxes based on vibration data.[7,24] This work has focused on the preprocessing algorithms (such as the WPT used in Ref. 23) that extract statistical features from the data that can be used for diagnosis. The feature extraction algorithms are used to extract features from new data, which can then be compared with features extracted from known nominal data and features extracted from data with various known failures in order to form a diagnosis. The choice of features to extract is motivated by knowledge of the underlying physics, so these methods are not purely data-driven. However, the knowledge used is not explicitly encoded in a model, so we have chosen to classify the methods as data-driven rather than model-based.

V. Model-based diagnosis

Livingstone is a model-based diagnosis engine developed at NASA Ames Research Center that reasons about system-wide interactions to detect and isolate failures.[25,26,27] Livingstone uses a hierarchical model of components and modules. Each component is modeled using a finite state machine. Livingstone has been successfully demonstrated on various space systems including the Deep Space One spacecraft,[28] the X-34 spaceplane,[29] the X-37 spacecraft,[30] and the EO-1 satellite.[31]

TEAMS is a commercial product from Qualtech Systems Inc. which primarily uses a model-based approach to fault detection and diagnosis, but also includes a data-driven component within its TEAMS-KB module.[32] Aaseng *et al*. used TEAMS to build a prototype ground-based diagnosis system for a portion of the power distribution system on the International Space Station (ISS).[33] The prototype they built is model-based and does fault detection and diagnosis. They have plans to extend it to prognostics and to include the data-driven approach.

VI. Model-based prognosis

Ray and Tangirala present a physics-based method for detecting cracks in metallic materials and predicting their remaining life. [34] Their models use extended Kalman filters and stochastic differential equations. They validate their models using induced faults from a laboratory setting.

VII. Conclusion

As stated in the introduction, fully implementing prognostics is very difficult. For realistic systems, fault detection is difficult, and prognostics – predicting the remaining time until failure – is much more difficult. Several authors have stated their intention to do prognostics, and have described the progress they have made in fault detection, but have left estimation of useful life remaining to future work. Much research has been done in the area of structural prognostics using data from vibration sensors, but we are not aware of any fielded systems in that area. There has been much more progress made in fault detection and diagnosis than in prognosis.

Most of the research reviewed here has not been fielded. Some are proposed architectures that have not yet been built (such as Refs. 14 and 16), some are systems that have been tested using synthetic data (such as Ref. 22), some are systems that have been tested using test stand data (such as Refs. 2, 4, 5, and 12), some are systems that have been tested using historical operational data (such as Ref. 19), and some are systems that have been tested using data from experimental flights (such as Ref. 21). Simulations and test stands offer the opportunity to simulate or induce faults that have never occurred in flight. Using real flight data, however, forces researchers to address all of the nuances that occur in real flight, such as noise and unexpected signals from unrelated subsystems.

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